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Limiting transportation sector greenhouse gas emissions: the role of system interactions on policy portfolio effectiveness

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Limiting Transportation Sector Greenhouse Gas Emissions:
The Role of System Interactions on Policy Portfolio Effectiveness

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Abstract

Significant cuts in global greenhouse gas (GHGs) emissions have been called for by numerous experts and science organizations to avert the negative effects of climate change. Light duty vehicles (LDVs) will play an important role in any new reduction policy due to their daily use, citizen reliance, and significant consumption of fossil fuels. Unfortunately, a single policy aimed at LDVs and one that results in the necessary reductions in a politically acceptable manner may not be possible. Instead, a policy portfolio approach may be needed. Implementing multiple policy mechanisms via a policy portfolio may create system effects that either reduce or enhance the effectiveness of these policies. This thesis evaluates the interaction effects among three possible GHG reduction policies: a carbon tax, fuel economy standard, and vehicle subsidies. The thesis applies a systems dynamic model to explore these interaction effects both qualitatively and quantitatively. The results demonstrate how GHG reduction policies should or should not be used in combination in order to maximize their effectiveness.

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1 Introduction

United States (US) decision makers are taking a fresh look at implementing new climate-energy policies in response to increasingly dire predictions of fossil fuel-driven climate change, reliance on foreign oil, and voters' pleas to reinvigorate the US economy by investing in "green industries". In doing so, it has become increasingly evident that there are complex impediments to creating a new US policy that addresses each of these issues.

On one hand, climate change experts have called for drastic reductions in greenhouse gas (GHG) emissions in the coming decades, yet there is no "silver bullet" policy capable of such actions. On the other, policy makers voice the need to wean the US off of foreign oil products, even though consumers tend to shy away from new fuel technologies due to higher cost and lack of necessary infrastructure. In order to realize these needs, each source of GHG emissions and fossil fuel consumption must be addressed individually. Further, multiple policies must be used to address the complexities within each of the systems that emit GHGs, so drastic cuts are guaranteed.

This study addresses how to understand these complexities and their interactive effects on policies by analyzing one portion of the emissions/fuel problem – the transportation sector. To accomplish this goal, two avenues are explored.

First, a more comprehensive approach of conceptualizing climate-energy policy proposals is demonstrated by using a systems dynamics (SD) framework. This provides both a qualitative and quantitative method of grooming multiple policies, or portfolios, that heed unintended pitfalls due to internal system feedbacks as well as take advantage of these feedbacks to maximize results. The Climate Legislation Impact Model for the Analysis of the Transportation Sector (CLIMATS) SD model is developed, producing reasonably accurate and usable data for policy analysis.

Second, three often cited transportation GHG reduction policies (fuel economy standards, vehicle subsidies, and a carbon tax) are analyzed individually and in combination for cases of interactive effects. An assessment of the portfolios that synergistically produce deeper GHG reductions when implemented in combination than if individually is made. Conversely, portfolios are assessed as to whether resistance is met and less GHG reductions occur when policies are implemented in combination.

Using CLIMATS, the analysis shows that policy makers can take advantage of system dynamics to produce greater emission reductions. Care must be taken though to heed a number of unintended consequences. Decision makers must implement a high enough policy magnitude to surpass policy resistance *plateaus* where meaningful reductions begin to occur only after a certain level. If the strategy is to take advantage of synergistic effects between multiple policies, decision makers must carefully choose a combination that falls within the *window of opportunity* where greater reductions are met. Further, policy makers should not assume that greater reductions will be met the higher the policy value is because system feedbacks can lead to additional marginal benefit plateaus, where an increase in policy does not lead to a decrease in emissions.

1.1 The Climate Change Conundrum

The most recent report from the Intergovernmental Panel on Climate Change (IPCC) unequivocally stated that global warming is occurring, human actions are behind the 0.8°C rise in global average temperature since the industrial revolution, and if mitigation steps are not taken immediately there will be significant consequences for much of the world (Pachauri and Reisinger, 2007). No previous report authored by a consensus of the world's most eminent scientists had been so certain or focused in their calls for action. Unfortunately, even with this consensus and changes in climate patterns, such as historic droughts (O'Driscoll, 2007), heat waves (Schar et al., 2004), and storm intensities (Trenberth and Shea, 2006), US policy actions aimed at resolving the issue have occurred slowly.

Decision making delays have enhanced the already perilous position policy makers are in due to the unique scientific characteristics of climate change. A lag in mitigating carbon dioxide (CO_2), the principal planet-warming GHG, only makes future policy decisions more difficult. CO_2 remains in the atmosphere between 100 to 500 years after its initial inception and only gradually decreases over time (IPCC, 2001). This *residence time* means that the longer emissions are allowed to remain high (above 350-450 parts per million atmospheric concentration), the longer the Earth's ecosystems will incur severe effects (Hansen et al., 2008; IPCC, 2007). For example, CO_2 emitted in the year 2000 will remain in the atmosphere through 2100 at over half the concentration, regardless of any new emissions reductions made in between.

The residence time of CO_2 also does not allow policymakers to *incrementally* reduce emissions over time (Sterman, 2008). If emissions are gradually reduced, in much the same way that many nations currently plan to do, global average temperatures will still continue to rise (Sawin et al., 2009). To avoid this, emissions need to be considerably reduced in the short term in order to stabilize climate patterns and "preserve a planet similar to that on which civilization developed and to which life on Earth is adapted" (Hansen et al., 2008; Matthews and Caldeira, 2008).

Historically, US federal policy has not reflected an understanding of either characteristic. In 2008, President George W. Bush enacted policies that projected a gradual halt in GHG growth by 2025 through voluntary technology changes, even though considerable temperature rise would still be locked in for the coming decades (Bush, 2008). Even more aggressive proposals pushed by current President Barack Obama do not fully take these scientific realities into account by delaying drastic cuts in emissions for another decade or more (Obama, 2008).

Clearly stated, the consequences of the CO_2 residence time are twofold: 1) the chosen policies of the US must be capable of accounting for a large percentage of GHGs and 2) the policies must reduce emissions in the short term and for a consistent time period.

Three questions arise from an emissions standpoint. First, how much do total GHG emissions need to be reduced? Second, when do total GHG emissions need to be reduced by this amount? Third, what public policies can be implemented to reduce emissions by the necessary amount and time?

The first two questions have been extensively studied by meteorologists and climate modelers for much of the past three decades (IPCC, 2007). The most recent climate modeling studies found that in order to *just stop* the increase of global average temperature and avert the more negative effects of climate change, GHG emissions must be reduced to "near-zero" by mid century (Matthews and Caldeira, 2008). A literature search of pertinent climate change policy reports from government agencies, the IPCC, and environmental organizations finds an 80% cut below 2005 levels by 2050 has generally been coined as the ideal reduction target, though the shape of the reduction (i.e. the annual rate of reduction between now and 2050) is uncertain.

An answer to the third question is less clear. Finding solutions that account for the CO_2 residence time (while being economically cost effective and capable of traversing political barriers both nationally and internationally) have been complicated by the absence of a "silver bullet" policy that if enacted would halt global warming (Bandivadekar and Heywood, 2004). In response, discussions have focused on individual policy levers that address specific GHG emissions sources, grouped by economic sector. Unfortunately, the climate change policy literature offers little guidance on what sectoral approach, both individually and in combination, will explicitly reduce total GHG emissions to near-zero. For example, a typical approach, offered by the Pew Center on Global Climate Change, reports that a "hybrid policy" consisting of a cap and trade system, carbon tax, and increased research and development funding for clean technologies is necessary (Nordhaus and Danish, 2003).

While short on reporting specific policies important to each emissions sector, the Pew Report offers an example (one typically seen in the literature) of how a climate-energy policy needs to be constructed as a "portfolio" of options. In addition, in their most recent report, the IPCC states that, "reducing emissions…requires a portfolio of policies tailored to fit specific national circumstances" (Metz et al., 2007). Researchers have also begun to respond to this need by shifting from individual policy analysis to portfolio analysis (Bandivadekar et al., 2008).

1.2 The Climate-Energy Policy Problem

To date, policies used to address climate-energy issues have largely been in the form of a patchwork collection of state actions, such as California's low carbon fuel standard (LCFS) and the northeast states Regional Greenhouse Gas Initiative (RGGI) cap-and-trade program. These efforts have acted as small scale, regional experiments, but have yet to transition into national policies (Byrne et al., 2007). To a lesser extent, policies nationally implemented decades ago to conserve US fuel supply are now being relied on to reduce GHG emissions and force the introduction of less carbon intensive technologies (An and Saur, 2004). For example, increasing the Corporate Average Fuel Economy (CAFE) standard for light duty vehicles has been a common recommendation for reducing transportation emissions in the US.

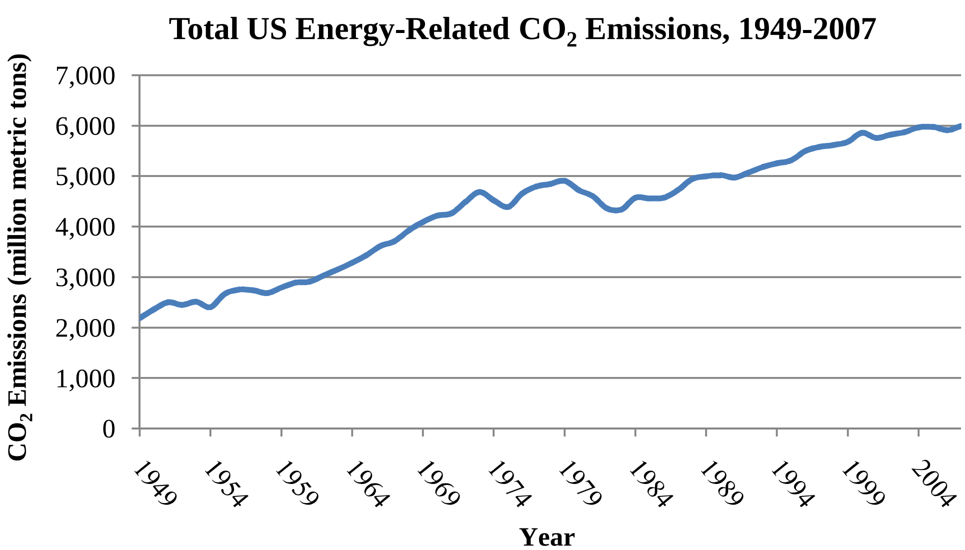

Figure 1 Total US energy-related CO_2 emissions for period 1949-2007 (EIA, 2007).

In both cases, neither has halted the increase in US emissions, shown in Figure 1, of roughly 1.8% annually (EIA, 2007a). More recent changes in US energy policy have altered traditional fuel efficiency standards for appliances and vehicles, increased the amount of alternative energy supply, and offered limited tax breaks for consumer energy conservation decisions like home weatherization. While broadly mitigating many sources of emissions, even these policies only optimistically project to *slow* the increase in CO_2 (EIA, 2009b).

Figure 2 illustrates these future projections, made by the Department of Energy (DOE) Energy Information Administration (EIA). Though the EIA assumes that the current economic recession and new legislative efforts stabilize emissions in the short term, CO_2 is expected to increase over time as each sector is expected grow. Predictions point to consumers continuing to demand more energy use to travel, businesses expanding their energy consumption, and industry recovering from the recession. The same holds true for fossil fuel consumption, in general.

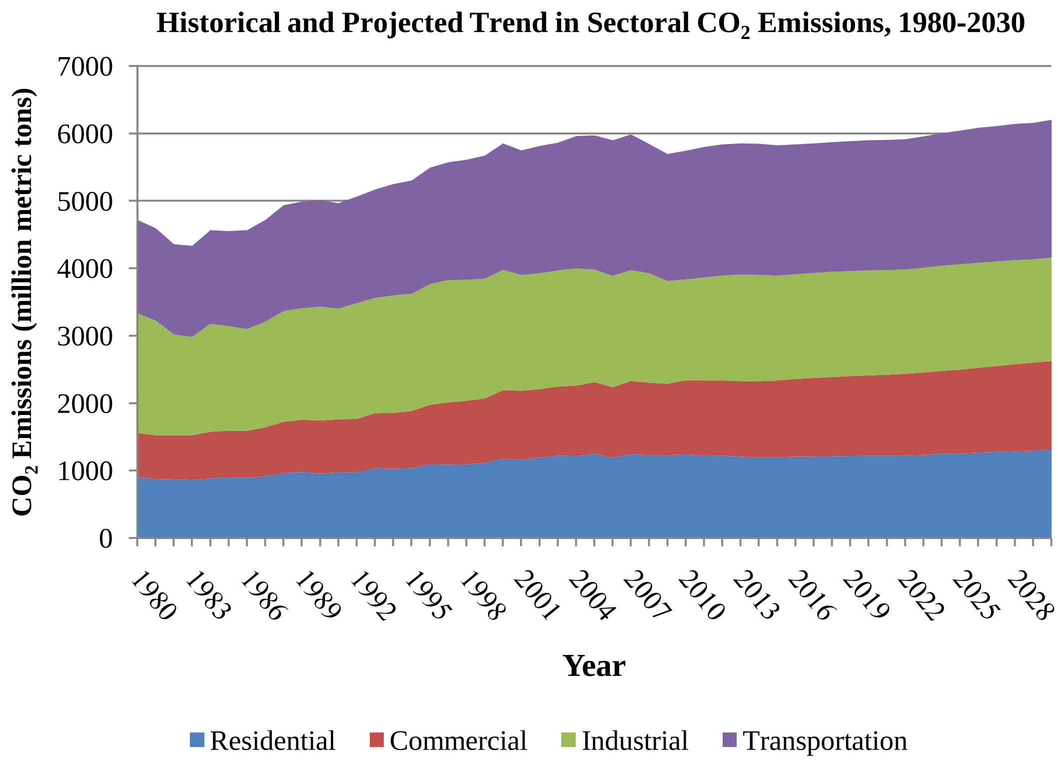

Figure 2 Historical and projected trends in sectoral CO_2 emission, 1980-2030, given assumptions of current legislative impact (EIA, 2009b).

Figure 3 and Figure 4 illustrates the annual consumption of petroleum by each sector. Historically, electricity generation has been the largest consumer of petroleum, but due to the oil supply shocks of the 1970's and the subsequent transition to coal and nuclear energy, petroleum product use has decreased in the past few decades. During the same period, drivers have consumed more transportation fuels by driving longer distances and less fuel efficient vehicles (as will be discussed in the following section). So, not only is decarbonizing electricity generation (be it from coal or oil) and addressing inefficiencies in residential and industrial energy use still needed, mitigating the burgeoning transportation sector is just as important. Due to this growing importance and the need to focus on a smaller portion of US emissions due to modeling and time constraints, this study is limited to the transportation sector.

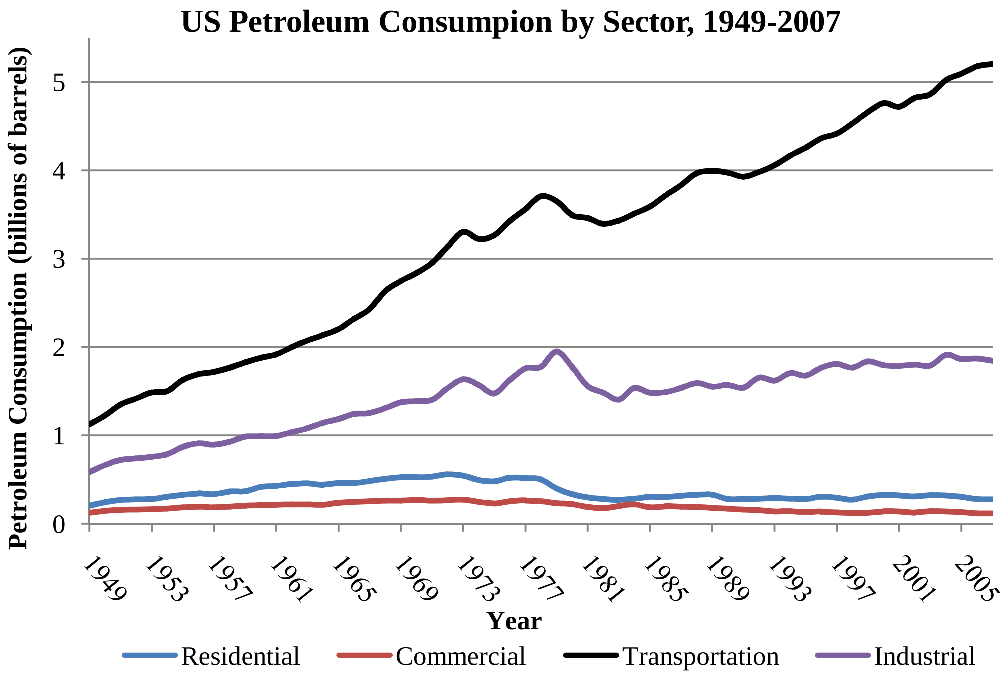

Figure 3 US petroleum consumption by sector, 1949-2007 (EIA, 2009).

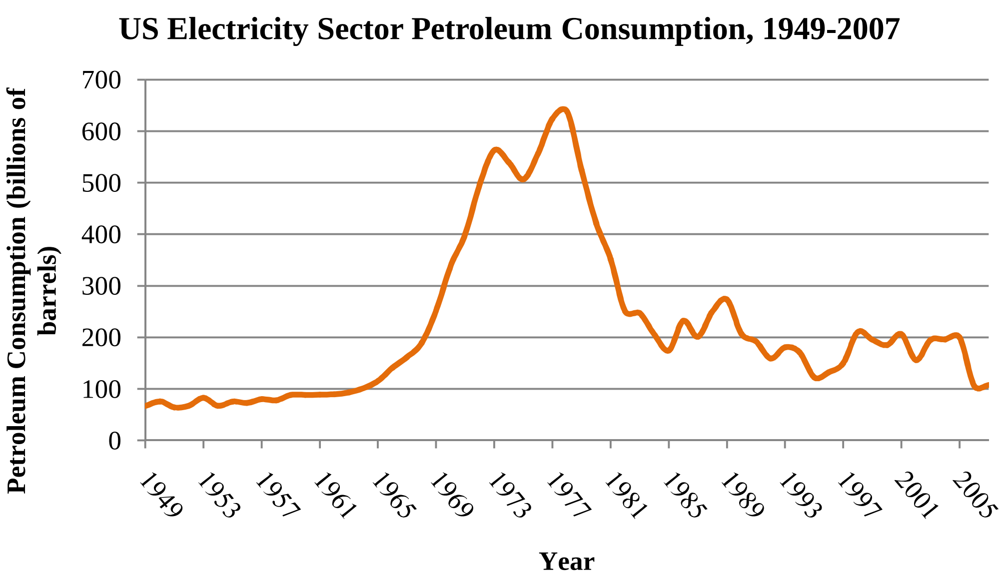

Figure 4 US electricity sector petroleum consumption, 1949-2007 (EIA, 2009).

1.3 The Transportation Sector and Greenhouse Gases

As shown in Figure 5, the transportation sector emits 33% of annual US CO_2 emissions, or 6.1% of the worlds output, making it a key target of any new climate-energy policy (EIA, 2008c, 2009b). The transportation sector also represents a unique policy case that has received considerable attention from decision makers, analysts, and scientists.

Vehicle emissions and fuels were a focal point for energy policy proposals during the 2008 presidential primary and general elections. The National Academies convened a number of expert panels aimed at recommending opportunities to reduce transportation sector emissions and energy use. Also, key science policy advisors to the US government have written extensively on methods and issues of reducing these emissions. Notably, Dr. John Holdren, current science advisor to President Barack Obama, and co authors wrote that the US must move away from the traditional status quo of just fuel efficiency standards to an all encompassing, multi instrument set of policies (Gallagher et al., 2007).

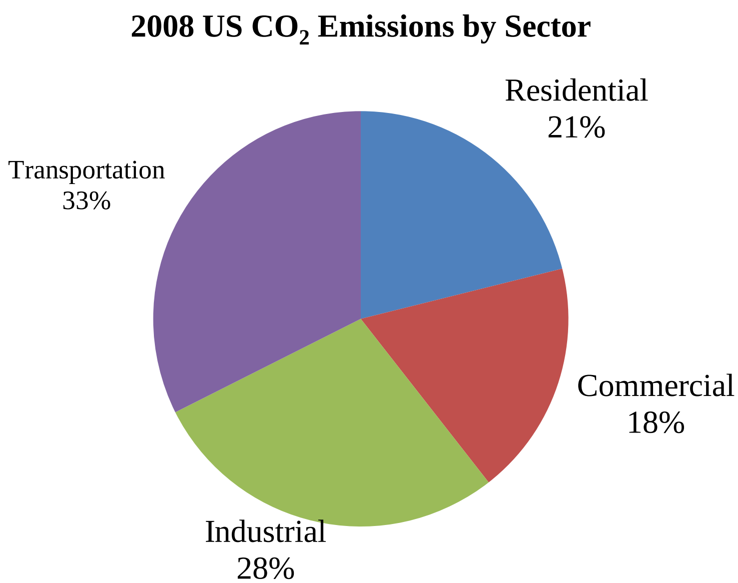

Figure 5 2008 US CO_2 emissions by economic sector (EIA, 2009).

A key impediment to policy making in the transportation sector is that it is comprised of a myriad of modes (e.g. freight, air, etc.), each used for different purposes. Figure 6 outlines and proportions annual CO_2 emissions by mode and shows that light duty vehicles (LDVs) or consumer transport vehicles less than 8500 lbs gross vehicle weight rating (GVWR), are the most prominent source of emissions. In addition, LDVs are the largest (in terms of number of vehicles) and the most commonly used mode of transportation. Other sources, such as water vessel shipping, rail, heavy duty trucks, and air travel collectively account for a less significant share of emissions and must be dealt with individually even if carbon reductions are sought through a sector wide cap and trade program (Arroyo et al., 2008).

Due to its majority share of CO_2 emissions, any transportation sector policy aimed at reducing emissions and fossil fuel use *must* include LDVs. Figure 7 illustrates that transportation emissions have increased over the past few decades, specifically by an average of 2.1% per year (Davis and Diegal, 2007). The source of this increase can largely be attributed to LDVs, which are also the most dynamic in terms of the number of variables acting to increase its share of importance.

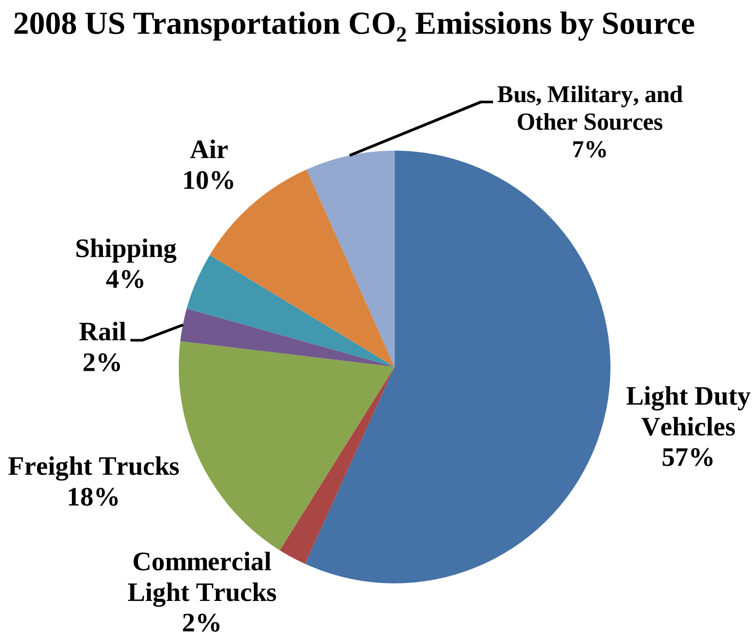

Figure 6 2008 transportation CO_2 emissions by mode (EIA, 2009).

Prominently, consumers have trended towards purchasing larger vehicles, such as sports utilities (SUVs) and pick-up trucks, which Figure 7 illustrates. Most striking is the multi decadal decrease in car use and their replacement by SUVs, which were not regulated by federal CAFE standards (only cars and pickup trucks through present day).

The transition to larger, unregulated vehicles (as well as a lack of increase in the CAFE standard over time) has been a significant reason the LDV population to stay wholly less fuel efficient. Most pronounced has been 220% growth in the number of trucks in use (compared to a 11% rise in cars in use), which are less fuel efficient than cars (Davis and Diegal, 2007). This trend coincides with the stagnation in the LDV population average miles per gallon since the 1980's, shown in Figure 8.

The same figure also displays that during the same time period there was a gradual increase in the distance traveled per vehicle. So the combination of consumers driving more and their vehicles being less efficient has led to a two-fold increase in annual LDV miles traveled (VMT) since 1980 (Figure 9, blue line).

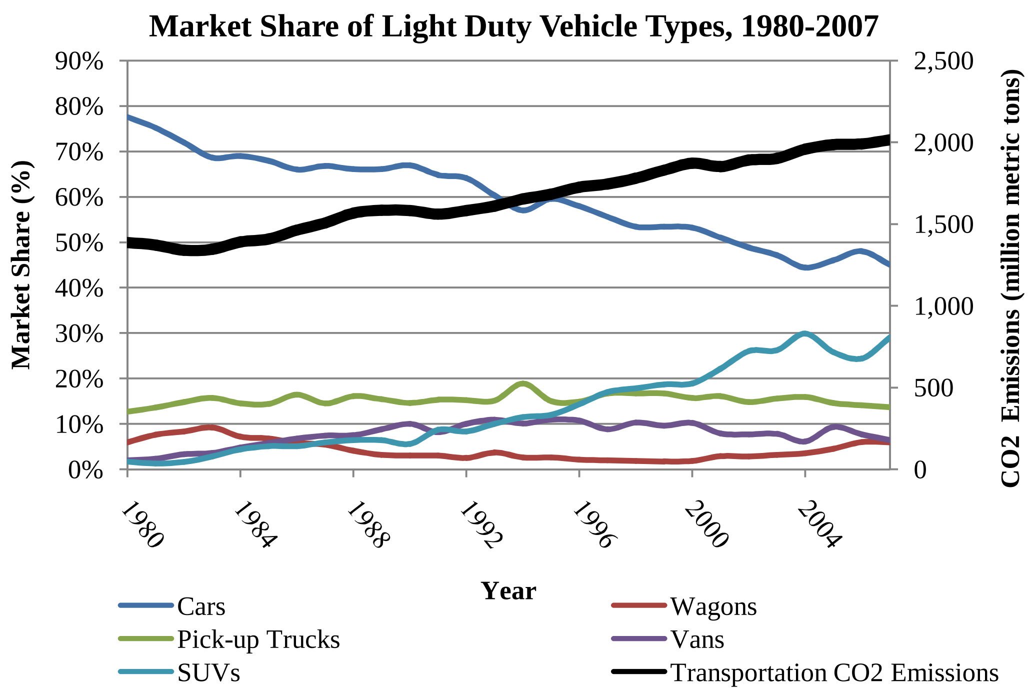

Figure 7 Market shares of light duty vehicle types, 1980-2007. Black line indicates transportation CO_2 emissions.

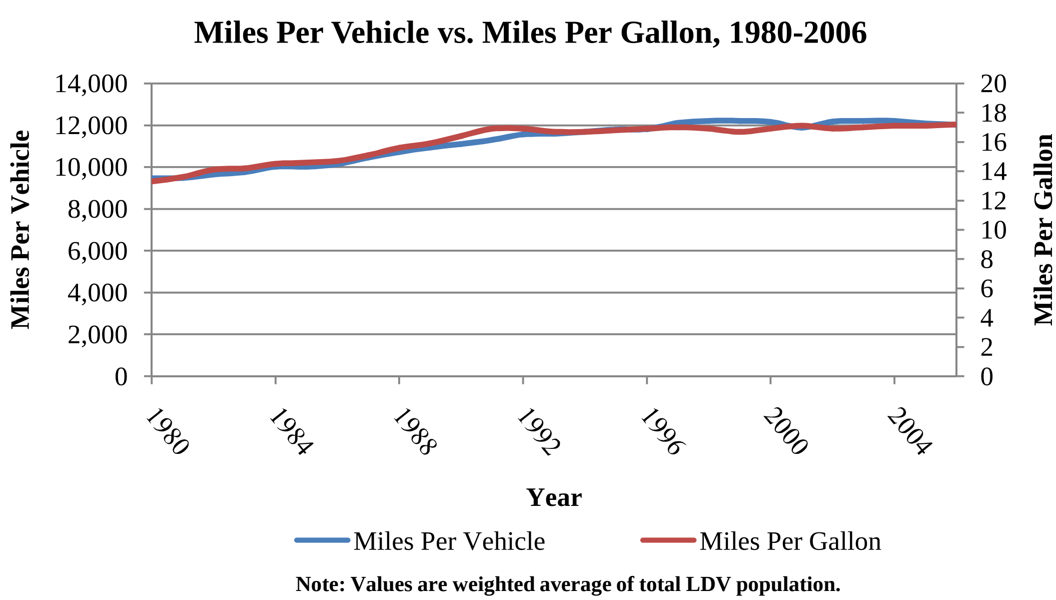

Figure 8 LDV population averaged annual miles per vehicle compared to average fuel economy, 1980-2006 (EIA, 2008b).

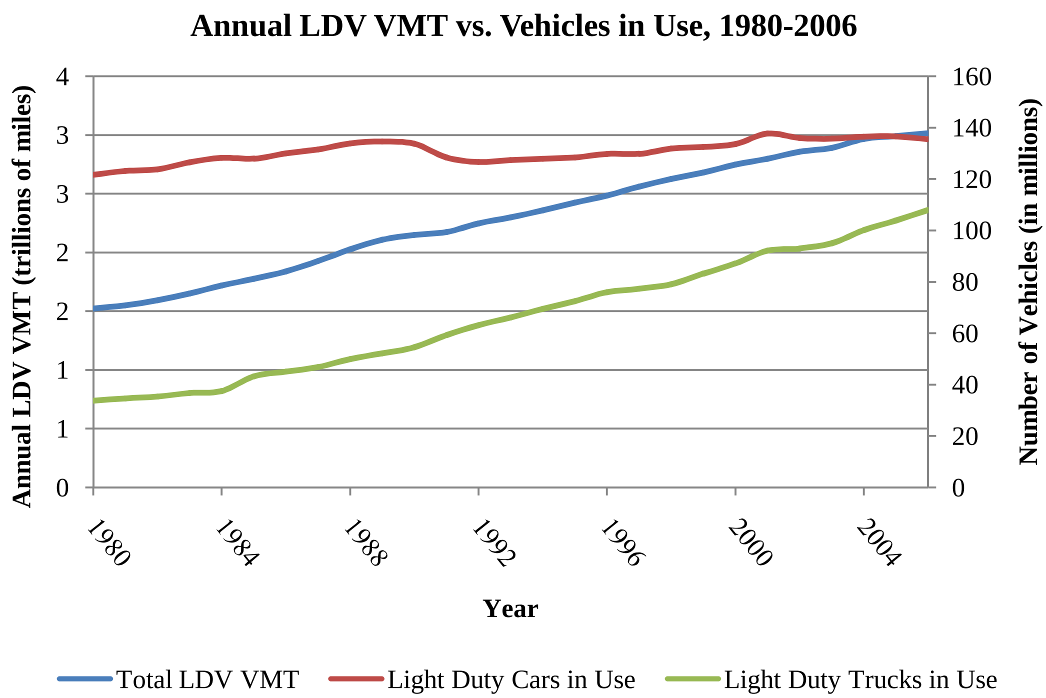

Figure 9 Annual LDV VMT, 1980-2008 (FHWA, 2009b).

In concert, these changes have fueled the growth in LDV, transportation, and US emissions. The variables that drive this annual increase are interrelated, but different, requiring individual policy attention. Dr. Holdren (as well as many other researchers and analysts) lists four key challenges of limiting transportation emissions within this context (Gallagher et al., 2007).

First, the combination of low fleet fuel economy and long vehicle lifetime creates two barriers to increasing the efficiency of the vehicle population and reducing LDV GHGs. Policy makers must recognize the *inertia* of turning over the vehicle population caused by consumers keeping their vehicles longer time periods. Policy makers must also account for what vehicles consumers choose to purchase and how they interact with car manufacturers. For instance, US consumers prefer more *powerful vehicles* (quantified as horsepower), which manufacturers have fulfilled possibly at the expense of new technologies that, all else equal, would have improved efficiency (Plotkin, 2000).

Second, the role of consumer choice in driving and purchasing decisions can significantly erase reductions in fuel consumption through an increase in VMT. Technological improvements can be made to increase efficiency, but emission and fuel consumption improvements can be overshadowed by drivers changing their traveling habits. Climate-energy policies must not forget to address consumers driving tendencies if deep reductions are meant to be made.

Third, the liabilities of alternative fuels could inhibit the market penetration of alternative fuel vehicles. From an emissions standpoint, the use of alternative fuels requires upstream fuel production emissions to be accounted for to ensure that policies are not shifting emissions from one source to another. A good example would be plug-in hybrid vehicles which rely on the electric grid, which largely produces coal emissions to charge its batteries. Extensive use of these vehicles may shift emissions from the tailpipe to the electric grid. Climate-energy policies must address the *entire* lifecycle of LDV emissions, both upstream and downstream.

Fourth, additional impacts of an economy-wide policy, like a cap-and-trade program, are likely to be limited, creating a greater need for further sector specific policies. Throughout the previous sections, the case that the climate change conundrum requires a drastic, short term, sustained cut in emissions was laid out, and it can only be met by addressing each emissions sector through specific policies. Just looking at one sector – transportation – it should be evident that the causes of emissions are many, unique, and complex and require a portfolio of policies to mitigate each of the variables responsible for GHG growth.

Any policy portfolio recommendation must take into account these challenges as well as any other techno-socio-economic feedbacks found in the transportation system that may be barriers to successfully limiting climate change (Bahrman et al., 2002; Fiddaman, 2007). An understanding of how "best" to construct these portfolios is imperative to providing credible, realistic, and usable input to decision makers and is the objective of this study. To do so, transportation feedbacks and challenges are modeled and the impacts of different climate-energy policies, both individually and in combination, are analyzed.

2 Feedback Effects within Complex Systems

In order to understand the transportation sector challenges facing policy makers, it is necessary to visualize the system as "complex". This allows for the discussion of feedbacks and policy interactions within a commonly accepted vernacular typically used to discuss large scale ecosystems and economies (Costanza et al., 1993; Sterman, 2000, 2002, 2008). In its simplest definition, a system can be thought of as a group of interacting, interdependent parts linked together by exchanges of energy, matter, and information. A *complex* system is typically characterized by "strong, often times non-linear, interactions between…complex feedback loops that make it difficult to distinguish cause from effect and significant time and space lags, discontinuities, thresholds, and limits" (Costanza et al., 1993).

Feedback loops are defined as a condition whereby the output of a system affects its inputs through a series of relationships (Deaton and Winebrake, 2000; Sterman, 2000). Two types of feedback structures are particularly important: *reinforcing* and *balancing*. A balancing feedback (also referred to as a counteracting or negative feedback) represents a condition whereby causal loops in the system cause a variable that is perturbed to ultimately seek its original value. Conversely, a reinforcing feedback (also referred to as a positive feedback) represents a condition whereby causal loops in the system cause a perturbed variable to respond in the same direction as the perturbation (Deaton and Winebrake, 2000). Complex systems may have both types of feedback loops, each with differing magnitudes.

The impact of many combinations and magnitudes of feedback loops can lead the system to exhibiting nonlinearities and lag effects when changes are made, defined broadly in this study as *interactive effects*. These causal effects confound policy makers by creating *unintended consequences*. An ideal example of this is federal fuel economy standards (CAFE).

CAFE standards for light duty cars and pick-up trucks have regulated the fuel economy (i.e. miles per gallon) of new purchases since 1978 and are an example of a policy that has not realized its intended purpose due to system processes. The regulation was enacted through the Energy Policy Conservation Act by Congress in 1975 to reduce energy consumption in response to the 1973-74 Arab oil embargo, which limited the US supply of petroleum products. Figure 10 plots the weighted combined CAFE standard for new cars and pick-up trucks (green line) as well as the total vehicle population fuel economy (red line) since 1949.

Clearly, there is a noticeable rise in the vehicle population's fuel economy post the standards implementation (to the right of the black line), but aside from a very short term decrease in fuel consumption (a fact also attributable to the high price of gasoline at that time) it did little in the long term (Plotkin, 2007). The goal of these regulations was to reduce energy use, but because it did not take into account other trends in the system, the policy had a smaller than intended impact.

Feedbacks such as vehicle population turnover, consumers growing preference for larger, more powerful vehicles (to be filled by unregulated SUVs and less efficient light trucks), or the increase in driving that occurred most notably after fuel prices dropped were originally not accounted for (Greene, 1997). Each of these system characteristics led to the *unintended consequence* of long term fuel consumption *increasing* instead of decreasing.

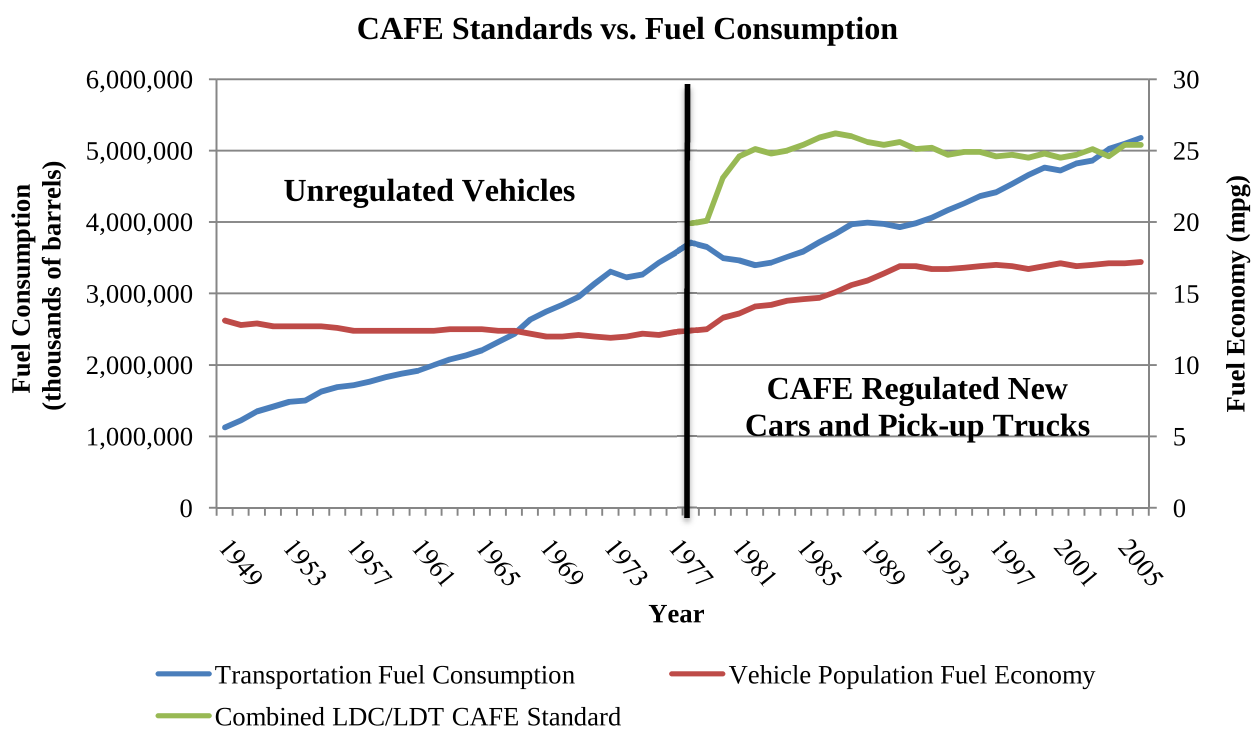

Figure 10 Historic transportation fuel consumption, 1949-2006, compared to the LDV populations fuel economy before and after CAFE standards were implemented (Davis and Diegal, 2007; EIA, 2007a, 2008b).

The existence of a potential set of unintended consequences due to feedbacks exemplifies the need for multiple policies in order to reach policy goals. It is here that the use of policy portfolios, previously argued as necessary to reduce transportation climate emissions, offer yet another unique opportunity for decision makers.

If feedback loops are identified and potential unintended consequences are known, a portfolio of complementary policies could be used to take advantage of the system and lead to a *more successful* policy outcome. Such *policy synergies* are defined as an interaction of two or more policies that, when combined, achieve policy goals more successfully than would be achieved by each policy separately. In contrast, the interaction of two or more policies in combination, where the combined policies lead to negative impacts that would not have occurred by either alone, are called *policy conflict* or *policy resistance* (Sterman, 2000).

When studying transportation sector policies, three sources of synergy can be considered: *complementarity*, *financial support*, and *public acceptability* (May and Roberts, 1995; Vieira et al., 2007). Complementarity occurs whenever the positive benefits or effectiveness of policies in combinations, such emissions reductions, are greater than if implemented individually. Financial support occurs when one policy is implemented in combination to fund another policy, such as taxing gasoline to pay for alternative fuel infrastructure. Public acceptability occurs if a policy is implemented in combination to provide an additional public incentive to accept a negatively viewed regulation. An example could be providing free public transportation if drastically increasing the gas tax.

For this study, complementarity policy synergies will be considered. The identification of feedback loops and by association potential unintended consequences is a key step in constructing synergistic policy portfolios that hold a greater opportunity to reduce GHGs and fuel consumption. Modeling climate-energy policy effects on the transportation system must be capable of sufficiently accounting for a complex system of feedbacks.

3 Transportation Sector Modeling Techniques

Choosing the correct modeling technique is a challenge. Limiting GHG emissions from LDVs requires a policy portfolio approach that compels the need to view and understand the transportation system as a complex mix of feedback interactions. To ensure that the chosen policy portfolio reduces GHGs by the necessary amount, opportunities to take advantage of synergies need to be exploited.

However, typical methods of studying complex systems and policy combinations are limited. A literature review of research on policy combinations, interactions, and portfolios used to analyze the climate change conundrum and climate-energy policies reveal a lack of properly assessing feedback loops.

3.1 Spreadsheet Modeling

A prominent methodology is the use of spreadsheet-based tabulation models. The U.S. Department of Energy (DOE) Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) model is a primary example. It accounts for total fuel-cycle emissions and energy use associated with different transportation fuels and vehicle lifecycles and is used to analyze transportation policies (Wang, 1996). Though ideal for studying policy impacts on one dynamic of a system (such as upstream fuel emissions), the spreadsheet approach can become unmanageable if model boundaries expand to include more and more system complexities. Accounting for the numerous interactions among transportation sector variables would also be difficult, largely due to the constraints of using a spreadsheet.

To analyze the impact of multiple dynamics, custom solvers are added. Unfortunately, this approach limits researchers and policy makers to see and understand the impacts of each dynamics because each are buried within the many solvers, thus weakening an LDV-wide policy portfolio analysis.

3.2 Energy-Economy Equilibrium Modeling

A more comprehensive, sector wide approach is code-based, market equilibrium models, such as the DOE National Energy Modeling System (NEMS). NEMS forecasts the US energy market and is used by the federal government to predict future impacts of policies. Each fuel market and economic sector is treated separately as a sub model and interactions are hardwired into the code and often times parameterized to solve for equilibrium (EIA, 2007c). Analysis of feedback effects in such a model would be difficult under these circumstances. Also, a NEMS-like modeling system is costly and time intensive, which for the purposes of providing usable and readily available analysis (as well as being feasible for this thesis) eliminates it as a choice.

3.3 Database Modeling

More usable approaches are database driven analysis packages, like SimaPro. Historically, this method has been used to conduct environmental impact assessments, such as technology changes to automobiles (Hertwich, 2005). In fact, database models are often used in combination with spreadsheet models like GREET to supplement research findings. Like GREET studies though, policy analysis using these models is limited to only one, narrow portion of a system, for example the impact of increased aluminum use in vehicles, and is not easily transferrable to larger, multi feedback systems (Tan and Khoo, 2005).

3.4 Integrated Assessment Modeling

The majority of policy studies found in the literature use a combination of many techniques. Traditionally, policy makers want recommendations in terms of cost *and* reductions, so most climate-energy studies assess policy options through integrated assessment models (IAM). IAMs are broadly defined as any model that combines scientific and socio-economic issues and can be an amalgamation of other smaller models, a large spreadsheet, or code based model (Kelly and Kolstad, 1998).

Since the IPCC expanded its purview to include socio economic effects of climate change, IAMs have been created in greater numbers to assess specific issues such as policies aimed at implementing carbon capture and storage technologies (Metz et al., 2005); the diffusion of new clean energy technologies (Gillingham et al., 2008); the effects of adaptation and mitigation policies on sea level rise (Tol, 2007); and geoengineering scenarios that could augment mitigation policies (Wigley, 2006). In general, these models are constructed to calculate the cost of a certain policy compared to total emissions reductions (Kelly and Kolstad, 1998).

Computationally, such exercises become very detailed and extensive, so modelers use generalization and simple representations of key dynamics. For instance, in order to provide an estimate of the effects of policies on a large economic market, like transportation, researchers analyze individual policies and not many interaction effects (Kelly and Kolstad, 1998; Tol, 2006).

In the past decade, though, IAM based studies have attempted to assess multiple policies. For example, Rose and Oladosu (2002) found that if a Kyoto style permit trading system were combined with a carbon sequestration program there would be a 42% drop in cost per metric ton of CO_2, compared to implementing the permit system alone. This "interaction effect" was calculated by inputting the cost curve for carbon sequestration *along* with the cost curve of the permit trading system, allowing the cost of CO_2 to change according to both curves (Rose and Oladosu, 2002). While this represents a model capturing one interaction between two policies, it shows the inherent weakness of this approach.

IAMs are traditionally specific to the economic effects of policy choices, so system feedback effects important to emissions reductions are lost (though it can be argued they are also important to cost modeling as well). By focusing more on economic cost than GHG emissions sources, *sector specific* policy regulations such as gasoline taxes, low carbon fuel standards, and efficiency standards have not been directly modeled and have instead been assessed qualitatively (Kelly and Kolstad, 1998; Tol, 2006).

Nadel et al. (2006) concluded that in order for current federal alternative vehicle tax incentive programs to be most effective in transforming the automobile market, a combination of policies would be needed, such as the inclusion of tax code reform. In this case, a portfolio of policies was proposed based on a qualitative understanding of the weaknesses of the central tax incentive policy, but not due to explicit policy interactions caused by feedback loops (Nadel et al., 2006).

In fact, individual feedback loops have been quantitatively studied, but often not within the larger context of a complex system. In one instance, a feedback that ties the magnitude of a carbon tax to the effectiveness of an energy campaign that introduces consumers to the climate-energy issue has been documented. Models have shown that if the energy campaign shows signs of voluntarily decreasing emissions, then the carbon tax can be lower than expected.

Conversely, if the campaign policy does not work, extensive mitigation time has been lost, resulting in the need for a greater tax (Pearce, 1991).

This lack of effectiveness in accounting for feedback loops enhances additional characteristics that limit climate-energy IAMs' ability to model the US transportation system. First, these models largely focus on international policies, like a carbon tax or cap-and-trade system, and not on more sector specific approaches. Second, the complexity of performing such a large scale approach has led many modelers to simplify a system's dynamics, providing increased uncertainty and less accuracy. Third, the studies often discuss policy interactions and feedbacks qualitatively, so the magnitude of impact is not discussed. For these reasons the IAM approach does not seem capable of addressing policy portfolios.

3.5 Systems Dynamics Modeling

The most promising and emerging methodology in climate-energy policy analysis is systems dynamics (SD). In the last few decades, SD has been used to increase the understanding of complex environmental issues, including emissions from agricultural practices (Anand et al., 2005); water resource planning (Saysel et al., 2002); and climate change policy and economics (Fiddaman, 2002; Naill et al., 1992; Nordhaus and Yang, 1996; Sawin et al., 2009).

SD has also been used to study the role of transportation technologies and policies. For example, SD models have been used to evaluate problems related to expanding the use of biofuels (Bush et al., 2008); understanding barriers and increasing the market penetration of various alternative fuel vehicles (Ford, 1995b; Gillingham and Leaver, 2008); exploring the modal mix of urban transportation systems (Han and Hayashi, 2008; Wang et al., 2008); evaluating potential carbon reduction policies (Piattelli et al., 2002); and, predicting the optimal financial structure of a state-run feebate system (Ford, 1995a).

The main advantage of using SD to study complex systems and analyzing policies is that it requires both *qualitative* and *quantitative* modeling. Historically, SD describes every day systems in terms of the non linearity, delays, and feedback loops that affect it – the lack of which is a key weakness of previously discussed methods (Sterman, 2000). The modeling process is specifically designed to point out possible policy synergies, resistance, and other unintended consequences (Sterman, 2002).

It also stresses *analytical rigor* by being iterative throughout the model creation process, while still keeping the ultimate goal of aiding decision making in mind. The result is to limit simplification, thus including more feedbacks, but within the context of the decision maker's needs. The first step is to create a qualitative, theoretical model of the system, otherwise called a *Causal Loop Diagram* (CLD). Variables are questioned as to whether they are exogenous or endogenous to the system and how they interact. Feedback loops and relationships are constructed and discussed with stakeholders and other researchers to ensure higher certainty and to develop case studies (Sterman, 2000).

The second step is to construct a quantitative model based on the CLD. The cases developed in the first step can then be enumerated and further policy analysis can be conducted. The result is a deeper understanding of the feedbacks that make up a complex system, how these feedbacks interact, and how specific public policies are impacted. Because the feedbacks are openly modeled (compared to NEMS, for example), discussing the impact of multiple policies becomes much clearer.

These strengths match up well to the modeling and portfolio analysis needs of the transportation sector. The growing literature, especially in the climate-energy discipline, alludes to its acceptance as a viable, usable, and accurate methodology. For these reasons, SD will be the technique of choice for this thesis.

However, this approach does have limitations. As with other modeling options, SD can become a large and unwieldy exercise. Confronted with a complex system like transportation, strict model boundaries need to be set to ensure a timely and usable model, which will exclude *some* feedback loops. While not ideal, it is necessary, and if done rationally and in discussion with relevant experts in the field, can still lead to an accurate representation of policy impacts. To accommodate this weakness, setting system boundaries will be a detailed task and discussed within the context of the qualitative CLD.

4 CLIMATS SD Model

The *C*limate *L*egislation *I*mpact *M*odel for the *A*nalysis of the *T*ransportation *S*ector (CLIMATS) uses SD techniques to simulate the impacts of climate-energy policies on LDV emissions and fuel consumption. CLIMATS has been developed in the Vensim Systems Dynamics © modeling software package (www.vensim.com).

The goal of the model is *not* to predict future characteristics of the US transportation sector. Instead, the model is meant to predict the magnitude of policy impact on annual transportation GHG production. The primary goals of CLIMATS are three-fold:

1. To qualitatively identify prominent feedback loops and variable interactions supportive of or detrimental to LDV climate-energy policy success.
2. To identify potential unintended consequences, policy synergies, and policy resistance decision makers should take into account when deliberating legislation.
3. To quantitatively explore cases of potential policy portfolios that may provide decision makers with greater opportunities to reduce transportation GHGs and fuel consumption.

To provide context before establishing the more complex CLD and model, a subsystem diagram is presented in Figure 11. This diagram depicts the primary subsections that influence LDV emissions, and is provided as a high-level guide to the more complicated CLD (Sterman, 2000). The justification for including these emission sources is discussed within each section of the CLD and reflects the iterative process of including and excluding different dynamics based on system boundaries. The complete CLD and detailed feedback loops are discussed in the following section.

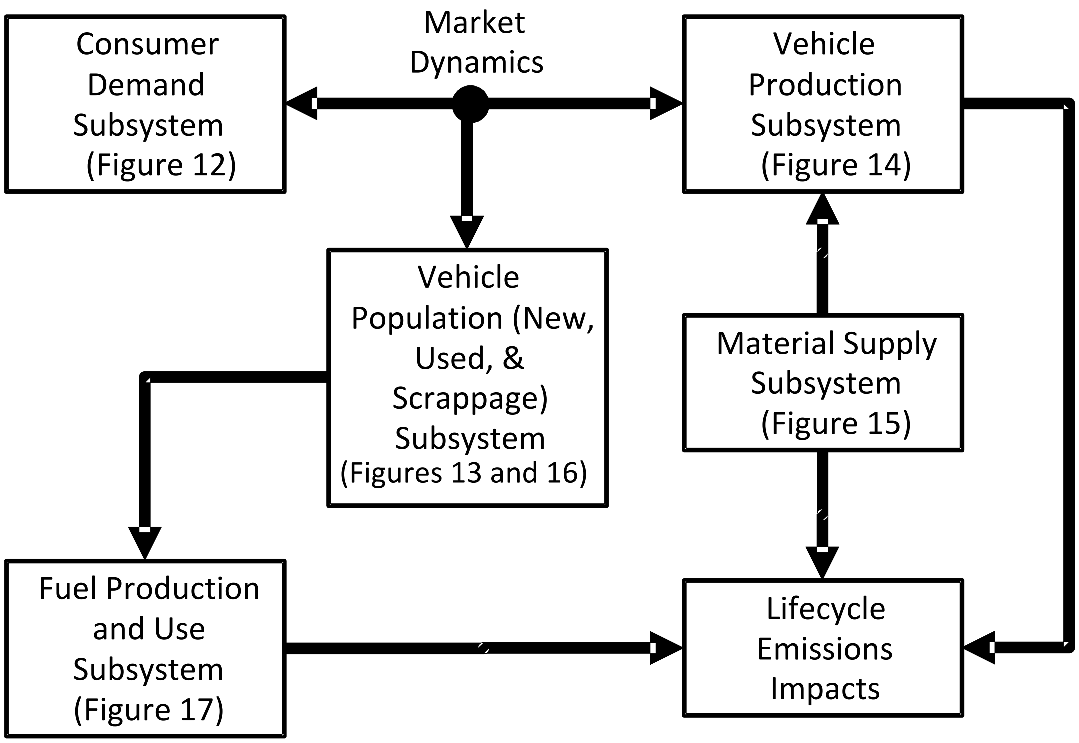

Figure 11 Subsystems represented in CLIMATS.

4.1 Causal Loop Diagram

The development of a CLD is strictly qualitative and heuristic in nature. It is here that systems modeling boundaries are set, feedback loops are identified, and potential dynamics (e.g. synergies, resistance, etc.) are explored. The CLIMATS CLD is complex, but through an investigation of its parts becomes easy to understand.

The major feedback loops are identified as are how each variable interrelates to one another through the use of text, arrows, and symbols. The interaction between two variables is represented by a causal connection (arrow running from the "cause" to the "effect") and a polarity (indicated by a "+" or "-"). The positive ("+") polarity indicates that perturbations in the "causal" variable will result in perturbations in the *same direction* as the "effect" variable, *assuming all else is held constant in the system*.

Similarly, a negative ("-") polarity on a causal arrow indicates that perturbations in the "causal" variable will result in perturbations in the *opposite direction* as the effect variable, again assuming all else is held constant. The causal relationships create feedback loops that are denoted as either balancing (B) or reinforcing (R) and each loop is given a name to facilitate discussion of the model (Sterman, 2000).

Simple text is used for variable names, with the exception of emissions variables, which are represented in boxes to quickly locate in the diagram. Also, causal arrows are not crossed to simplify presentation, so duplicate variable names are used in several places and are noted by brackets (<>).

4.2 CLIMATS System Boundary

Setting system boundaries is the first step in creating a CLD and is always a challenge (as is modeling in general). The boundaries are set through an iterative process and are a function of the research questions for which the model is designed to address (Liu et al., 2008). As the model's network of interconnected variables increases, its complexity and data costs grow exponentially – while usability and transparency often decrease (two important features to maintain for these types of integrated models) – so careful attention to model boundaries are imperative (Liu et al., 2008).

In this thesis, the CLD is developed heuristically, where each iteration considers model boundary expansion based on the goals of the model, answers to specific system boundary questions (presented below) and the judgment of experts in the field. Ultimately, the CLD exhibits a set of interconnected sub-systems and cause-and-effect loops that interact in complicated ways.

The CLD, and thereafter the quantitative model, explores the long-term, decadal scale impacts of GHG reduction policies on total LDV emissions. The GHG reduction policy literature provides a good overview of what portions of the total transportation system, or vehicle lifecycle, can be affected by policies and should be included. Based on this, Table 1 organizes a wide variety of policy mechanisms according to the vehicle emission lifecycle stage it mitigates (Claes, 2007).

The lifecycle aspects of the climate change conundrum and climate-energy problem are important in terms of vehicle production, use (e.g., fuel and material consumption) and disposal (Bandivadekar et al., 2008). Hence, CLIMATS needs to at least capture market behavior (consumers and producers), materials, and technologies used in different stages of the vehicle lifecycle. In addition, many emissions reduction policy options are focused on changing consumer purchasing and producer decisions, such as giving tax breaks for production of a specific technology (e.g., hybrid electric vehicles). Therefore, consumer/producer decision making needs to be considered as well.

Stage of Product Lifecycle	Command-and-Control	Market-based
Supply Chain Policies	• Regulate supply chain logistics	• Subsidize/ tax certain material inputs
Production Policies	• Mandate standards (technology forcing mandates) • Mandate technology use (technology driven mandates) • Regulate production process activities	• Subsidize or give tax breaks for the production of certain product types
Product Use Policies	• Restrict certain types of product use • Regulate product use	• Subsidize/ tax inputs necessary for product use
End-of-Life (EOL) Policies	• Mandate EOL practices (e.g. recycling mandate) • Regulate EOL practices	• Subsidize/ tax EOL activities

Table 1 Vehicle lifecycle policy categories and examples.

Given these broad vehicle lifecycle boundaries, set by discussing policy mechanisms, the following questions are answered to hone, justify, or eliminate variables that are candidates for inclusion.

1. *Complementary behavior, materials, or technologies*. Are there certain behaviors, materials, or technologies that are <u>complementary</u> to or <u>conflict</u> with the policy interventions being studied? For example, if evaluating the impacts of policies that affect vehicle efficiency (e.g., CAFE standards), system boundaries should capture behaviors, materials, and technologies that are complementary to or conflict with meeting regulatory expectations, such as the production and use of lightweight materials in new vehicle designs.
2. *Substitute behavior, materials, or technologies*. Are there certain activities, behaviors, or artifacts that are <u>substitutes</u> to the policy interventions being studied? For example, if evaluating the impacts of a fuel carbon tax, system boundaries should capture behaviors, materials, and technologies that can act as substitutes for the regulated behavior, such as the use of alternative fuels or vehicles.
3. *Temporal aspects*. Are there important <u>lag effects</u> or long time horizons that must be considered in relation to the policy interventions being studied? For example, if evaluating the impacts of policies that affect vehicle fleet turnover rates, system

boundaries have to extend out into the future long enough to capture these turnover effects.

By continually challenging each variable with these questions, the CLD takes form. The following section discusses each of the loops within the context of the subsystem diagram presented in Figure 11, paying careful attention to the justification for including each variable.

4.3 Complete System CLD

The CLIMATS CLD contains eleven identified loops, two of which are reinforcing and nine balancing, and is presented in Figure 12. For a summarization of the variables, loops, and descriptions discussed in the CLD, see *Appendix 1*.

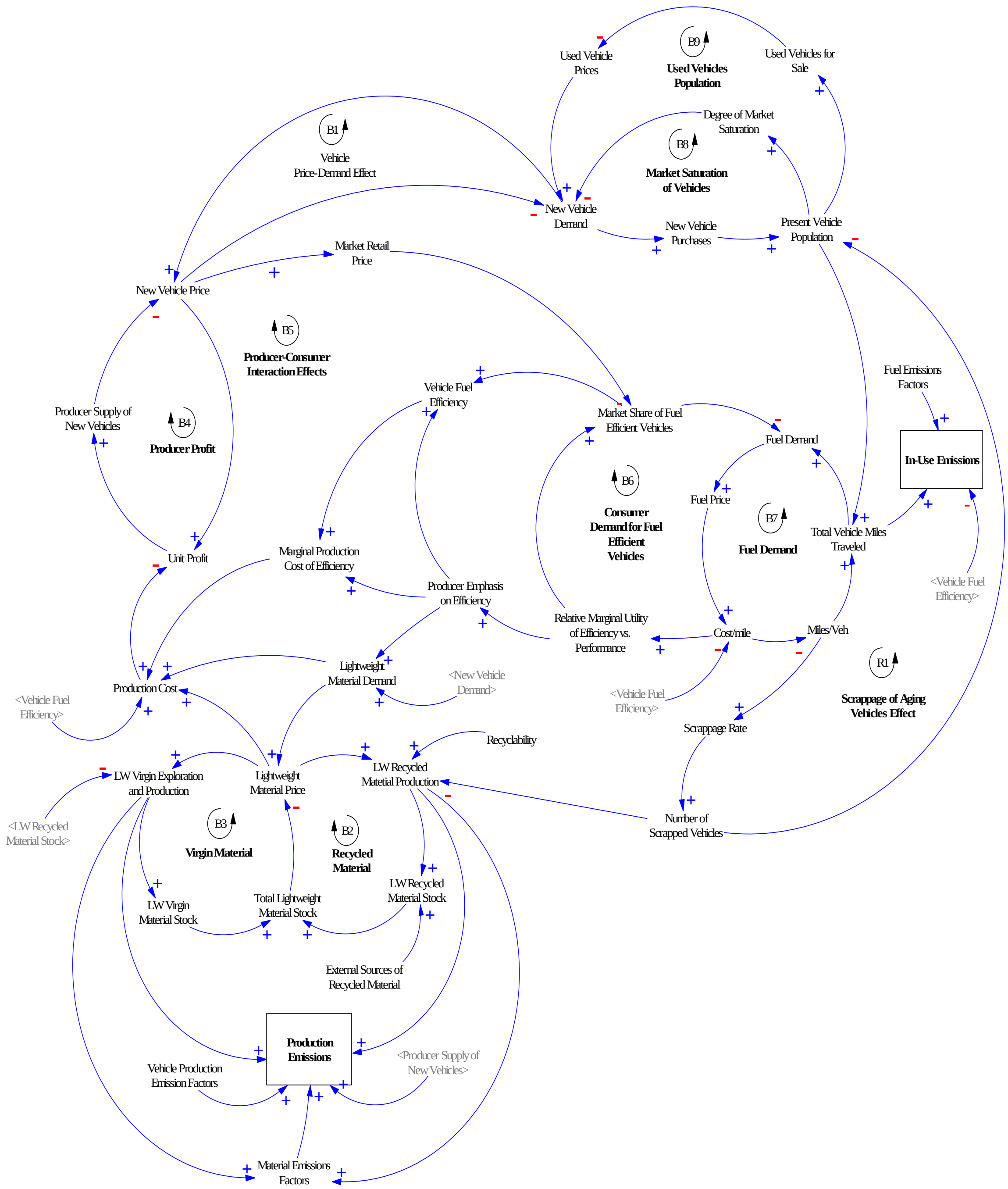

Figure 12 Complete CLIMATS CLD.

4.3.1 Consumer Decision-Making Loops

Since GHG mitigation policies may ultimately be aimed at either changing consumer behavior directly or changing the attributes of products that consumers purchase, capturing consumer decision making is important. Three loops help capture the cause and effect relationships that affect vehicle purchase decision making by a consumer.

Consumer preferences for vehicles are influenced by a number of factors including price, performance, fuel economy, size, safety features, and other attributes. For ease of discussion, there are three attribute categories that are particularly important: vehicle price, performance, and fuel economy (Berry et al., 2004; Mau et al., 2008). A longer, more detailed list of consumer preference variables will be outlined in the quantitative model, but for the purposes of discussing the CLD, only the most important are necessary.

The loops reflect the decisions consumers make among these three categories of vehicle characteristics through utility. Utility, or the level of desirability of the consumption of a good, dictates what choices are made when well known assumptions in economic modeling are considered (Berry et al., 1995, 2004; Greene et al., 2005; Turrentine and Kurani, 2007).

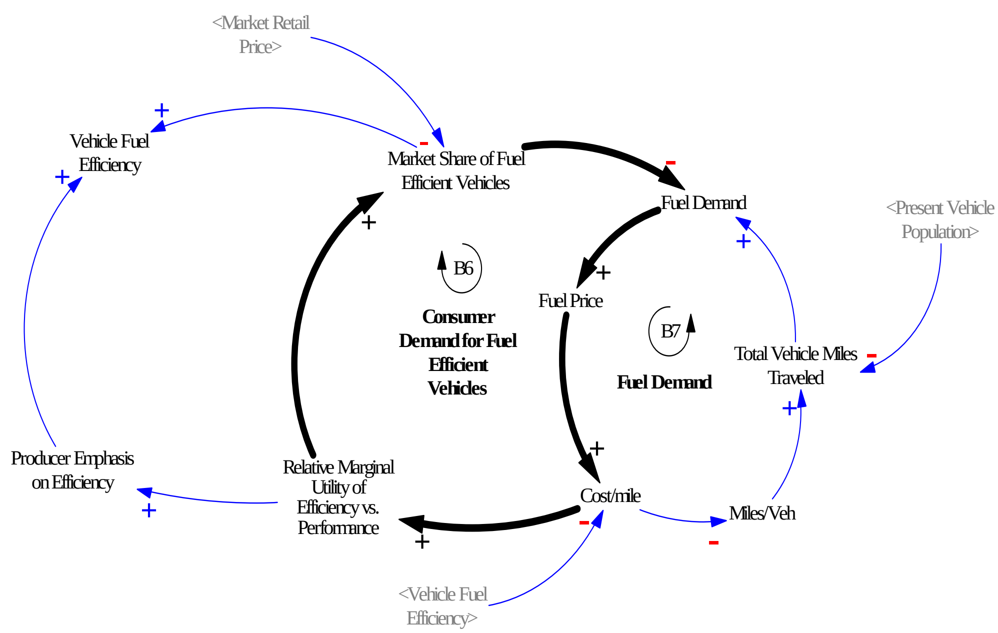

Figure 13 Consumer Demand for Fuel Efficient Vehicles Loop.

Figure 13 represents the *consumer demand loop for fuel efficient vehicles*. US consumers have historically made purchasing decisions that emphasized performance over fuel economy. However, as shown by the recent increase in fuel prices (i.e. cost/mile), consumers are starting to turn towards more fuel efficient vehicles (Morris, 2008). This implies a positive correlation between fuel prices and the relative marginal utility of fuel efficiency in consumer decision making.

Fuel demand is dependent on the number of miles traveled and the average fuel efficiency of the vehicle population. The fuel economy of the vehicle population is dependent on the market share of fuel efficient vehicles; under a fixed VMT, this market share is negatively correlated to fuel demand. Economically, fuel price is positively related to fuel demand, and in turn fuel price determines the cost of traveling per mile. Therefore, because fuel demand is intrinsically tied with the population of fuel efficient vehicles, perturbations in either will produce an individual balancing effect. Lee and Ni (2002) provide a good summary of the relationship between oil price changes (e.g., oil price shock in the 1970's and 1980's) and the automobile industry, demonstrating this balancing feedback (Lee and Ni, 2002).

Loop *B6* in Figure 13 captures this phenomenon. As the consumer's marginal utility of fuel efficiency increases compared to the marginal utility of performance, more fuel efficient vehicles are purchased, and the market share of fuel efficient vehicles increases. Loop *B6* is informative in that it shows how policies aimed at increasing the number of fuel efficient vehicles on the road may involve balancing feedback loops related to fuel prices that reduce consumers' willingness to pay for such vehicles.

Additional portions of the CLD model illustrate the relationship between new vehicle demand and the market share of fuel efficient vehicles. Figure 14 represents two feedback loops (*B8* and *B9*) that depict the dynamics between used vehicle (bold arrows) and new vehicle markets (dashed arrows). In this case, the purchase of new vehicles leads to increased availability of used vehicles (after a lag effect). The lagged increase in used vehicle supply will affect markets for new vehicles in later years, by providing a potentially less fuel efficient, less costly purchase option for vehicle buyers (Sterman, 2000).

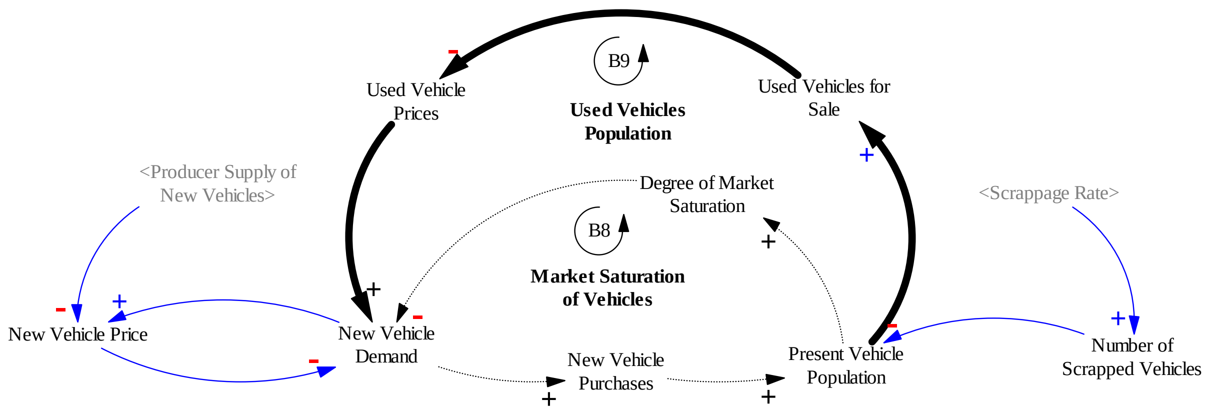

Figure 14 New and used vehicle purchase loops.

4.3.2 Producer Decision-Making Loops

Automobile manufacturers play an important role in determining the type of vehicles that consumers ultimately choose to purchase, as well as setting the initial prices that consumers will pay for such vehicles. Automobile producers need to make their decisions in the context of both consumer demands and government regulation (e.g., fleetwide fuel efficiency standards). Figure 15 depicts how the CLD models the relationships that affect producer decision-making.

Specifically, the interactions of supply, demand, and price are encapsulated in loops *B1 and B4*. Prices are set by the interaction of the negative effects of supply *(B4)* and the positive effects of demand *(B1*), bridging the gap between consumer and producer decision-making. Market price is determined when the two feedbacks equilibrate and the quantity of vehicles supplied equals the quantity demanded (Ackerberg et al., 2006; Berry et al., 1995).

The producer profit loop (*B4*) captures the influence of profit on producer decision-making. This profit is a function of other elements in the system model, such as production cost (which is further influenced by government regulation, technology and material choice, and other factors). Many recent studies have identified relationships between performance, cost, and other vehicle attributes, particularly with respect to alternative fuel vehicles (Austin, 1999; Energy and Environmental Analysis, 2002; Greene and Plotkin, 2001). To maximize profits, firms will produce vehicles with attributes that meet consumers' preferences as defined by their utility functions (see Figure 13 for example).

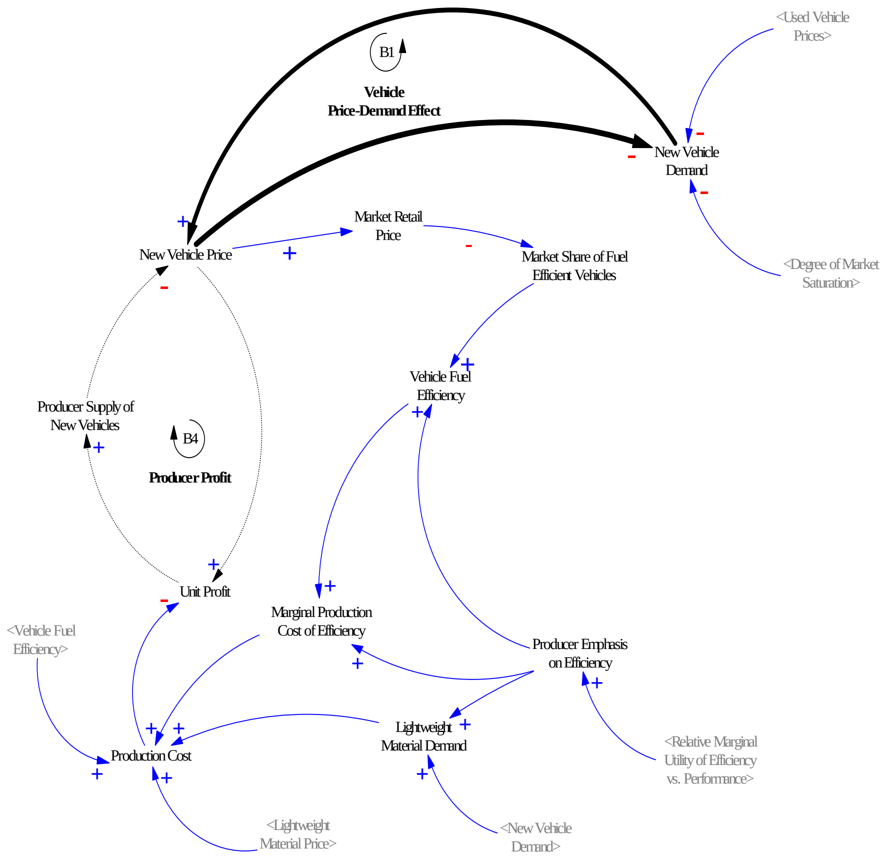

Figure 15 Vehicle supply, demand, and profit loops.

As an example, consider the role that material selection plays on producer and consumer decision-making. Figure 16 shows two loops related to lightweight material (e.g., aluminum) selection; lightweighting is one method producers can use to improve vehicle efficiency (Kim, 2008; Klimisch, 2007; Saur, 1995). Loops *B2* (bold line) and *B3* (dashed line) represent recycled lightweight material and virgin lightweight material decisions, respectively. As shown in the CLD, decisions on whether to use virgin or recycled material are dictated by supply (material stock) and price (influenced by availability and demand). These elements are, in turn, influenced by a number of other variables, such as recyclability and vehicle scrappage rates (Kim, 2008). Price differentials that may exist between recycled and virgin material are ignored and instead the same price for both virgin and recycled lightweight material is assumed. This is a simplification that restricts the use of this CLD for exploring policies aimed at influencing market prices for recycled and/or virgin material. However, the CLD does imply that such policies could have an effect on lifecycle vehicle emissions through material selection.

Therefore both downstream and upstream impacts can be assessed when considering such policies directly impacting material selection.

For example, virgin aluminum production emits 30%-40% more CO_2 than steel production. As a result, policies aimed at forcing vehicle manufacturers to increase the fuel economy of new LDVs may lead to production emissions increases if those policies or manufacturer decisions choose lightweighting strategies that consume aluminum. Alternatively, recycled aluminum or recycled steel presents much lower production emissions compared to their virgin counterparts (Das, 2000). Policies simultaneously encouraging use of recycled material where technologically feasible can reduce these emissions. The CLD allows decision makers to explicitly identify these relationships in order to understand how decisions related to recycling, can affect overall lifecycle emissions of autos.

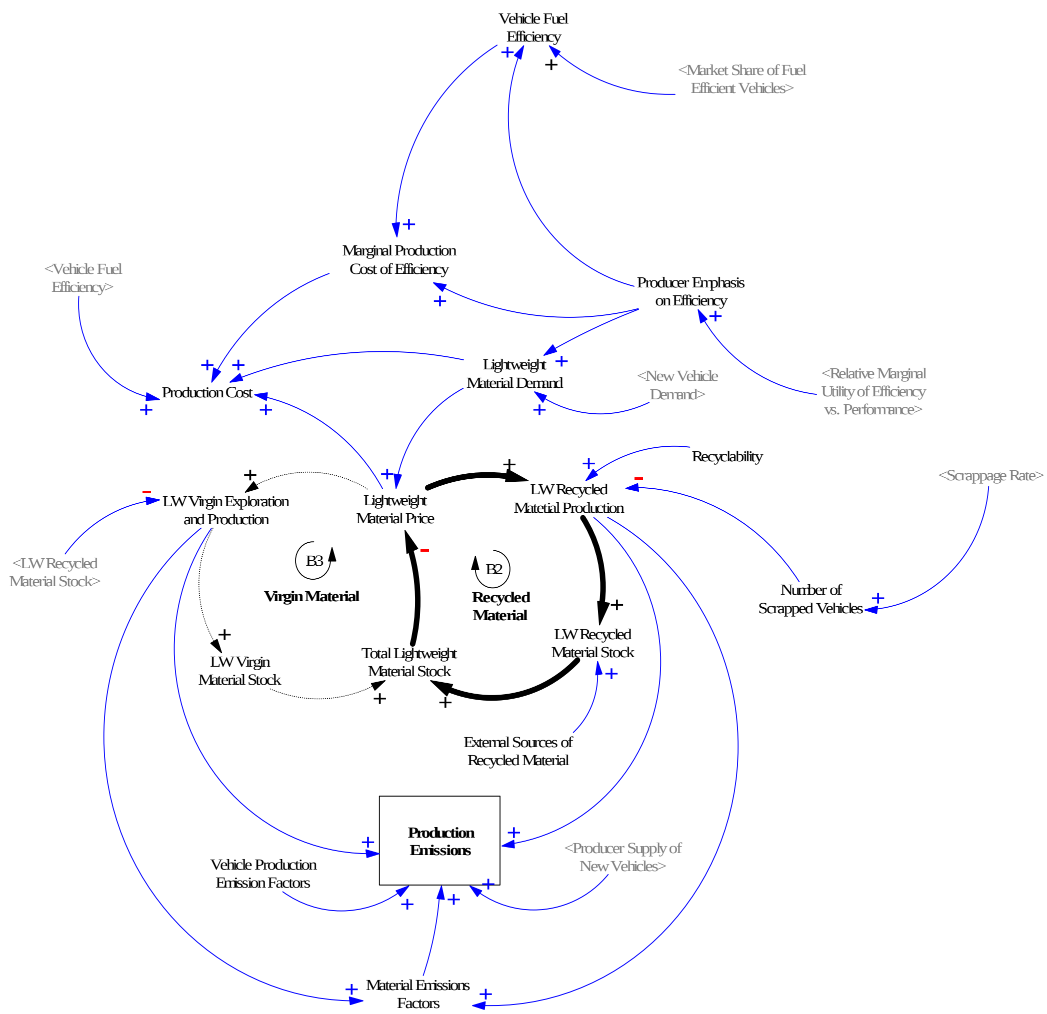

Figure 16 Recycled and virgin material production loops.

4.3.3 Vehicle Use Loops

GHG mitigation policies for the transportation sector have been primarily focused on vehicle use, since the vast majority of emissions come from the operation stage of the vehicle lifecycle. Loops *R1* and *B7* in Figure 17 and Figure 18, respectively, identify the relevant variables that impact vehicle operation emissions. Some of the key determinants of operational emissions from a fleet of vehicles include total vehicle population, average VMT, and average vehicle fuel economy. Indirectly (also shown in Figure 17 and Figure 18), fuel demand and prices affect VMT, and vehicle populations are affected through the consumer and producer decision loops presented earlier. Again, the CLD demonstrates how changes in fuel price not only can *directly* influence emissions (through the VMT relationship), but also can *indirectly* influence emissions by stimulating changes in consumer decision making that ultimately affect the attributes of the vehicle population.

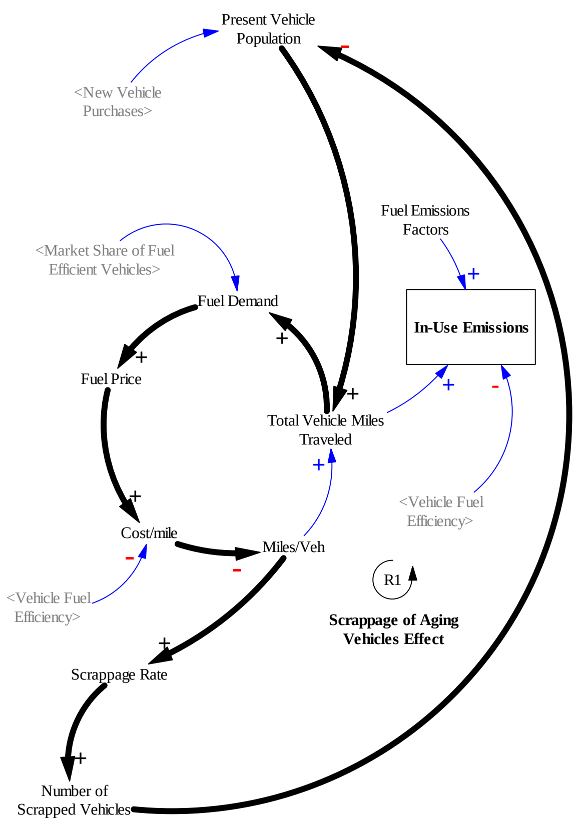

Figure 17 Scrappage of aging vehicles loop.

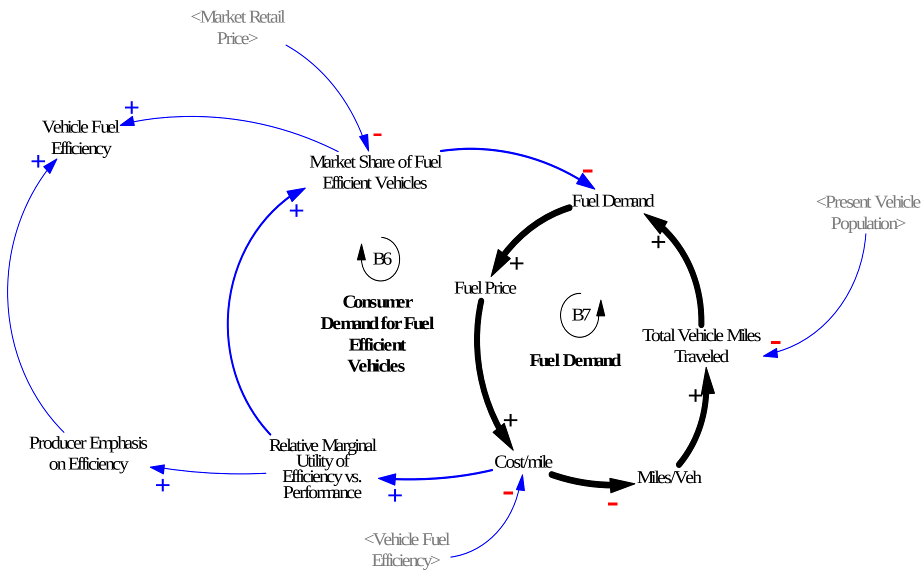

Figure 18 Vehicle fuel demand loop.

4.3.4 Omitted Loops and System Dynamics

By now, it should be given that the CLD contains many interrelated dynamics important to transportation GHG emissions policies. In upcoming sections, this detailed *qualitative* understanding of system dynamics will play a key role in analyzing policy portfolios. It should also be understood that the CLD is not a *full* representation of the LDV transportation system. Other feedbacks, variables, and dynamics have been omitted in an effort to make this first modeling effort manageable and timely, but still provide quality information to decision makers. Ideally, the CLD and its companion quantitative model should be considered and evaluated within an iterative and progressive process.

With that said, omitted dynamics will be considered *exogenous* in the quantitative model. Parameterization of these exogenous variables will be conducted, so dynamics will be contained within average values or growth rates if considered necessary and rational. Pertinent literature sources will be used to justify these parameterizations. Descriptions of these exogenous variables and dynamics will be discussed along with the model as a whole.

4.4 CLIMATS Quantitative SD Model

The next step in the SD process is to transition to a quantitative model. Figure 19 illustrates how each subsystem of the CLD was translated to CLIMATS.

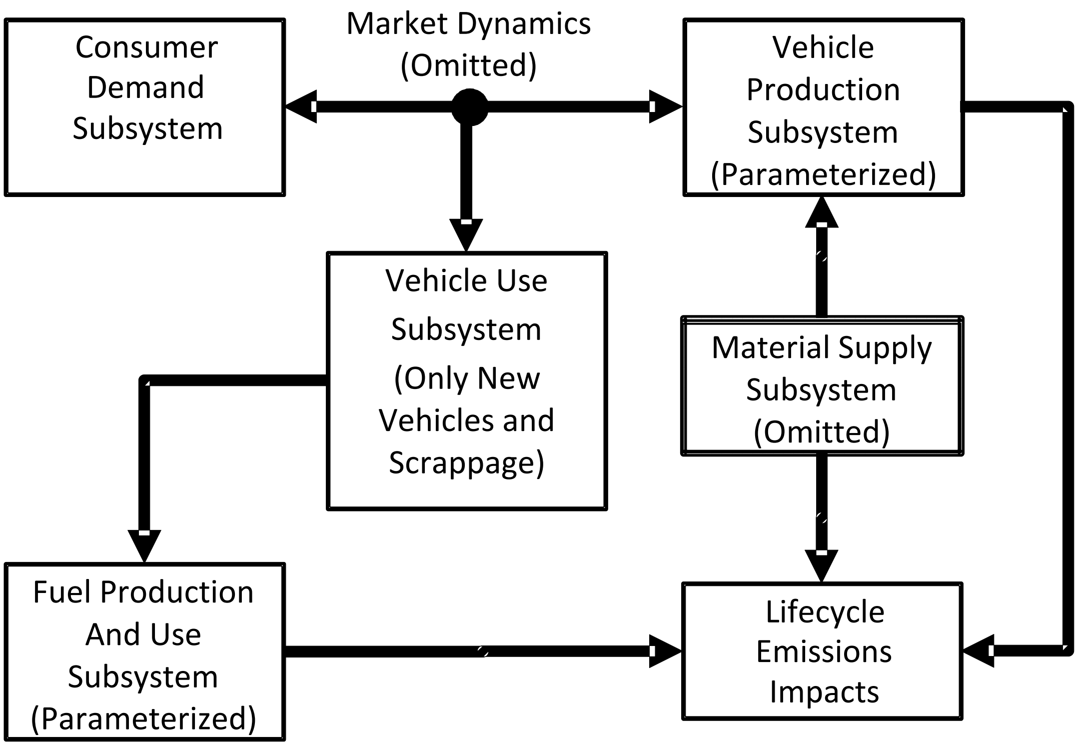

Figure 19 Subsystems included in the CLIMATS quantitative model.

As each feedback, variable, and dynamic were parsed out from the CLD and researched for use in CLIMATS, it became obvious that not all could be constructed and validated with reasonable accuracy and within a reasonable time. For example, macroeconomic market dynamics are not included in order to omit having to explicitly model both national and international dynamics. A literature search found that entire SD modeling projects have been undertaken to accurately simulate macroeconomic effects (Nordhaus, 1993; Sawin et al., 2009). A coparallel modeling effort of this magnitude is therefore outside the bounds of this project.

Due to this omission, feedbacks directly affected by economic factors must be altered. The used vehicles market (Figure 14) is omitted from the model due to its reliance on macroeconomic forces, like household income and unemployment. Some studies have modeled the used vehicle market as an "average" percentage of the total vehicle market (Goldberg, 1995). Given this inconsistency in the literature, the decision was made to narrow the focus of CLIMATS to the new vehicle market.

Similarly, the *Material Supply* feedbacks (Figure 16) were omitted due to a lack of readily available data and literature on internal system dynamics. Research is ongoing on this issue, but at the time of this study it was not complete, so modeling or parameterization could not be undertaken with reasonable accuracy (Kim, 2008). The same issue arose for the vehicle production subsystem of feedbacks (Figure 15). In order to include an accurate representation of vehicle manufacturing decision making and their interaction with consumer preferences, new computer software infrastructure needs to be developed to integrate external models for use with Vensim. This capability is under research and development, but not complete. Regardless, producer decisions can be made exogenously, where users input vehicle characteristics to test different modeling scenarios. It is understood that because these vehicle characteristics are now user inputs, greater care in choosing those attributes must be taken.

Even with these omissions, the SD quantitative model includes a number of realistic transportation system dynamics that when simulated in concert will build on the existing literature discussed in *Section 3 Transportation Sector Modeling Techniques*.

4.4.1 Vehicle Classes and Fuel Types

The core necessity of the quantitative model is to be able to simulate a number of technologies and fuels important to the LDV market. Table 1 outlined different policy levers important to emission reductions, which included forcing new vehicle technologies into the market. The majority of these policy levers attempt to address the main source of CO_2 emissions – vehicle operation – so what vehicles are being driven and purchased are vitally important. Fortunately, the Vensim modeling software is functionally capable of simulating numerous vehicle types simultaneously without the burden of additional, excessive coding.

Variables can be sub categorized or *subscripted*, so computations only have to be explicitly coded once, but are repeated for each variation. Building off of the data illustrated in Figure 7, CLIMATS includes different vehicle sizes or *classes*. Whether a consumer purchases a larger, less efficient or a smaller, more efficient vehicle is a key dynamic to capture. Also, CLIMATS includes a number of alternative fuel vehicle technologies, or *types*, so scenarios can be run testing how a policy changes the penetration of various vehicle types.

System boundaries dictate what classes and types to include in the model. For instance, producer dynamics, such as how far in development a technology is currently situated, are not captured, so vehicle types that are not predicted to enter the market in the coming decades in the AEO 2009 Update report are not included. Instead technologies that the literature suggests are more realistically capable of becoming commonly used are modeled.

Aside from conventional gasoline vehicles, diesel, flex fuel ethanol (FFV), and hybrid electric (HEV) vehicles are already available for sale (Figure 20) and have been the target of numerous climate-energy policies aimed at increasing each technology’s market share (EIA, 2009a). Conversely, due to the lack of a natural gas fueling infrastructure and the current lack of federal policy support for compressed natural gas vehicles on the same magnitude as electric driven engines, gas-based vehicle technologies is not modeled.

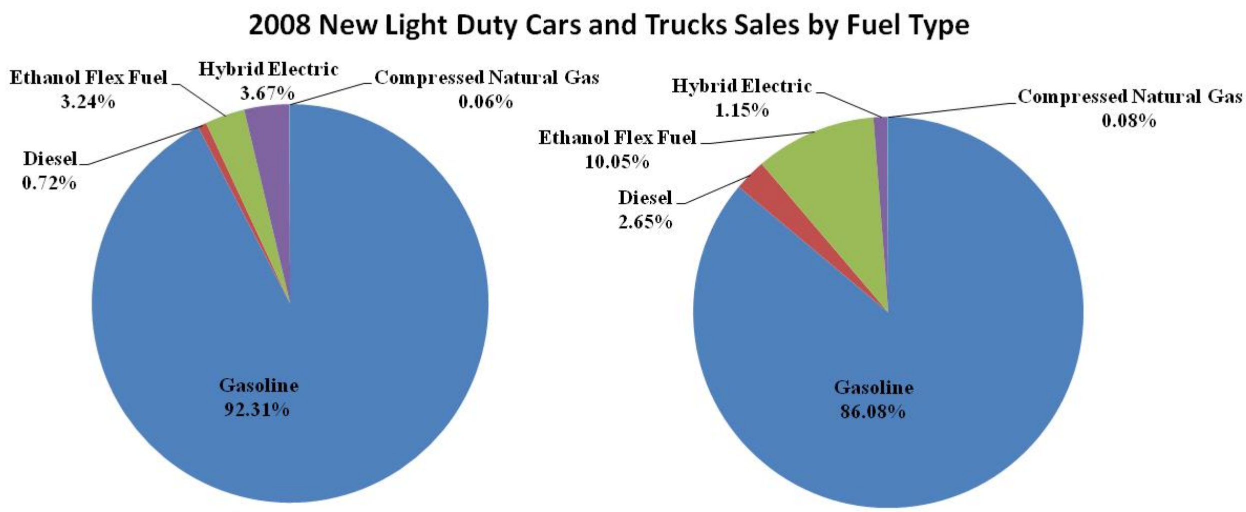

Figure 20 Percentage of 2008 new light duty car (left) and truck sales (right) by fuel technology (EIA, 2008a).

In addition, CLIMATS includes plug-in hybrid electric (PHEV) vehicles due to its prominence in the most recent Energy Independence and Security Act (2007) and the vehicle technology literatures suggestion that its market penetration will increase to almost 6% (from 0% present day and to an even greater share depending on future energy costs) by 2030 (EIA, 2009a).

The same process of justification can be used to choose a reasonable set of vehicle classes. Referring to Figure 21, two seat sports vehicles and minicompact cars can be omitted from the model due to each representing less than 2% of annual market share (the smallest of all classes) and thus not playing a significant role in LDV emissions.

A survey of available fuel efficient vehicles and expert predictions of the viability of vehicle technologies indicate that vans will be constrained to a significantly small share of FFV and diesel sales (and possibly be introduced as HEV technology) (EERE, 2009a). Energy Information Administration (EIA) data also indicates that vans are not expected to grow in population share in the coming decades (EIA, 2009a). Due to this perceived limited impact on the alternative fuel vehicle market, vans will also be omitted from CLIMATS.

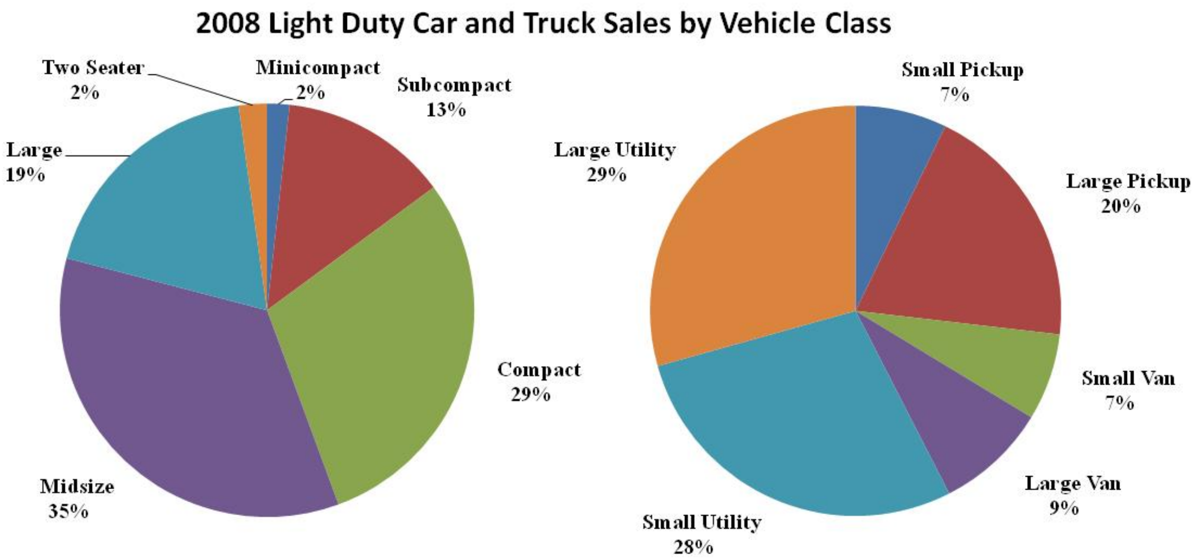

Figure 21 Percentage of 2008 light duty car (left) and truck sales (right) by vehicle class (EIA, 2008a).

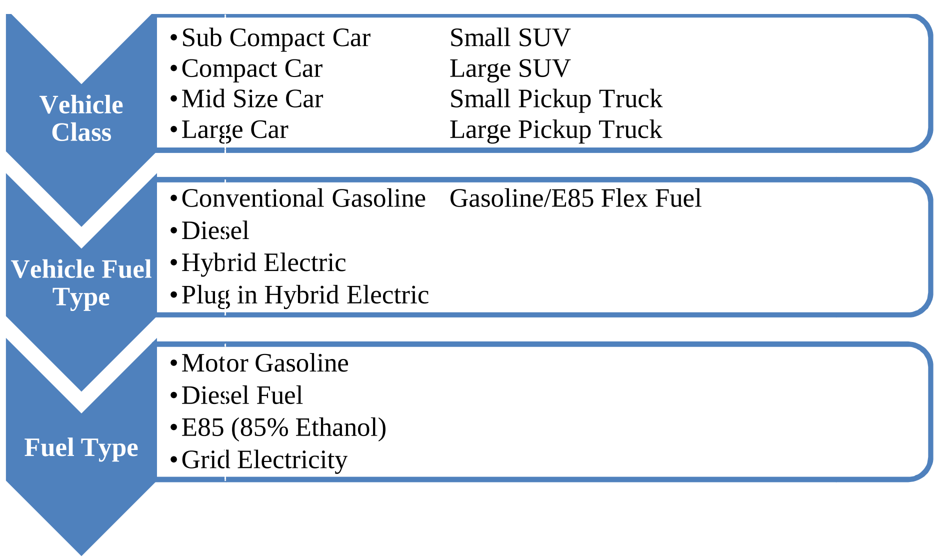

Figure 22 Vehicle class/type and fuel type category hierarchy.

Combining these modeling choices, CLIMATS will include the vehicle subcategories listed in Figure 22, where vehicle fuel types are subcategories of each vehicle class and fuel types are subcategories of each of those combinations. The choice of fuels was constrained to only those used by the vehicles being simulated. Vehicle class classifications are defined in *Appendix 5.2.1*.

4.4.2 Modeling Syntax

The CLIMATS syntax is similar to the CLD because both use the same Vensim software package. All variables included in another variable's equation are connected by arrows. In an effort to not inundate users with an excessive number of arrows, only connections that represent important relationships are shown. Connections needed to make sub calculations or manipulate data are not explicitly shown, but are included in calculations. For the same reason, variables in brackets (< >) represent duplicates that are used as placeholders in situations where either connecting variables would result in crossing other arrows or if the variable exists in another model section.

Simple text is used for *auxiliary variables*, or those that compute general equations during each time step. Boxes represent *stock variables* that act as accumulators. Data inputted into a stock variable is integrated over the simulation time and are a necessity for tracking the sum of a variable during a simulation. Data entering (addition) or exiting (subtraction) a stock variable are denoted by larger, double sided arrows and are called *flow variables*. All three variable types are used differently to represent complex dynamics in CLIMATS. An explicit listing of the equations and descriptions for each variable can be found in *Appendix 2.2*.

The subscript system described previously allows for simplifying how users interact with the SD model. Instead of having duplicate variables for each vehicle class and type, one variable is associated with all reproductions, allowing for a simpler comprehension of the inner workings of the model. Viewing subscripts can easily be done by clicking the variable in the model user interface.

Navigating CLIMATS is also streamlined by separating variables into three discrete *pages* or sections: *User Input Page*, *Cohort Submodel and Emissions Calculations Page*, and *Consumer Choice and Fuels Submodel Page*. The following sections will describe these pages by discussing the dynamics found within each as well as how the user interacts with the quantitative model.

4.4.3 User Input Page

Upon opening CLIMATS, the *User Input Page* loads, showing a listing of all user inputs. Each variable is thoroughly described in *Appendix 2*, so an explanation of the list will not be repeated here. Instead, brief instructions on how to navigate simulations are provided:

1. Before running the model, the simulation time must be set. Click on *Model* and then *Settings* and change *Final Time* to increase or decrease the length of the simulation. The base case scenario is set at 24 years.

2. To begin, users click the 'SynTheSim' button on the toolbar. This will automatically run the base case scenario and allow access to a menu of input options for each variable.

3. Once in simulation, the user can customize base case assumptions and values to reflect different scenarios by clicking the *slider* arrows associated with each variable. Figure 23 is a screenshot of the *User Input Page* while in simulation (note the double sided arrows associated with each variable).

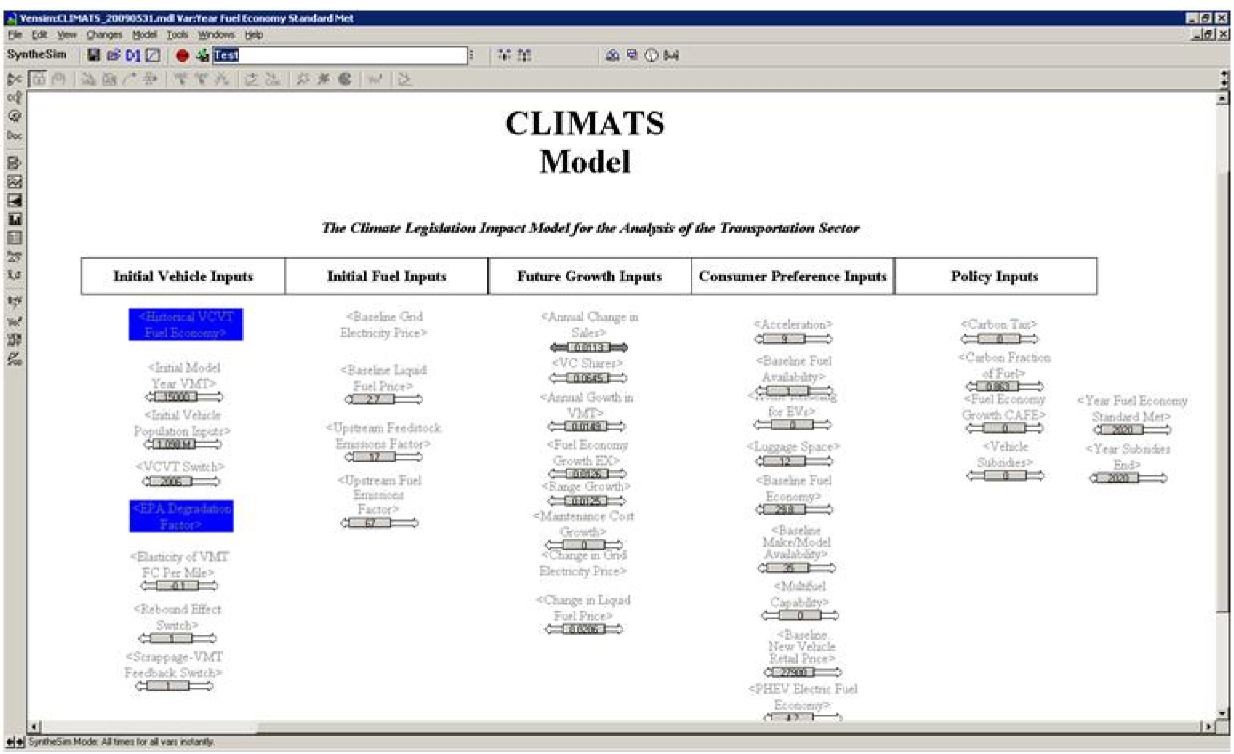

Figure 23 CLIMATS *User Input Page.*

4. User can change a total of 35 variables, which are outlined in *Appendix 5.1*. For simplicity, they are arranged in five categories:

a. *Initial Vehicle Inputs* represent variables that initialize and directly control the Cohort Submodel (described in *Section 4.4.4*). Here, initial vehicle population conditions (i.e. fuel economy, population, and model year VMT) can be changed and vehicle classes and vehicle types can be turned 'on' or 'off' or be forced to enter the model during a specific year. Also, the rebound effect and scrappage-VMT feedbacks can be turned 'on' or 'off'. Both will be defined and described in the coming sections.

b. *Initial Fuel Inputs* are variables that dictate initial fuel prices and emission factors for upstream fuel production and feedstock processes.

c. *Future Growth Inputs* are variables that force an exogenously driven change to simulate processes that are parameterized in the model.

d. *Consumer Preference Inputs* list new vehicle attributes that can be changed by the user.

e. *Policy Inputs* are explicit policy variables for a Carbon Tax, Fuel Carbon Content, and Vehicle Subsidies/Tax. This does not represent the only policies that can be currently tested using the model, just variables used to more easily discern policy effects.

5. When variables are clicked users can change inputs for all available subscripts through a drop down menu, shown in Figure 24. Also, maximum and minimum values can be set for any future sensitivity analysis.

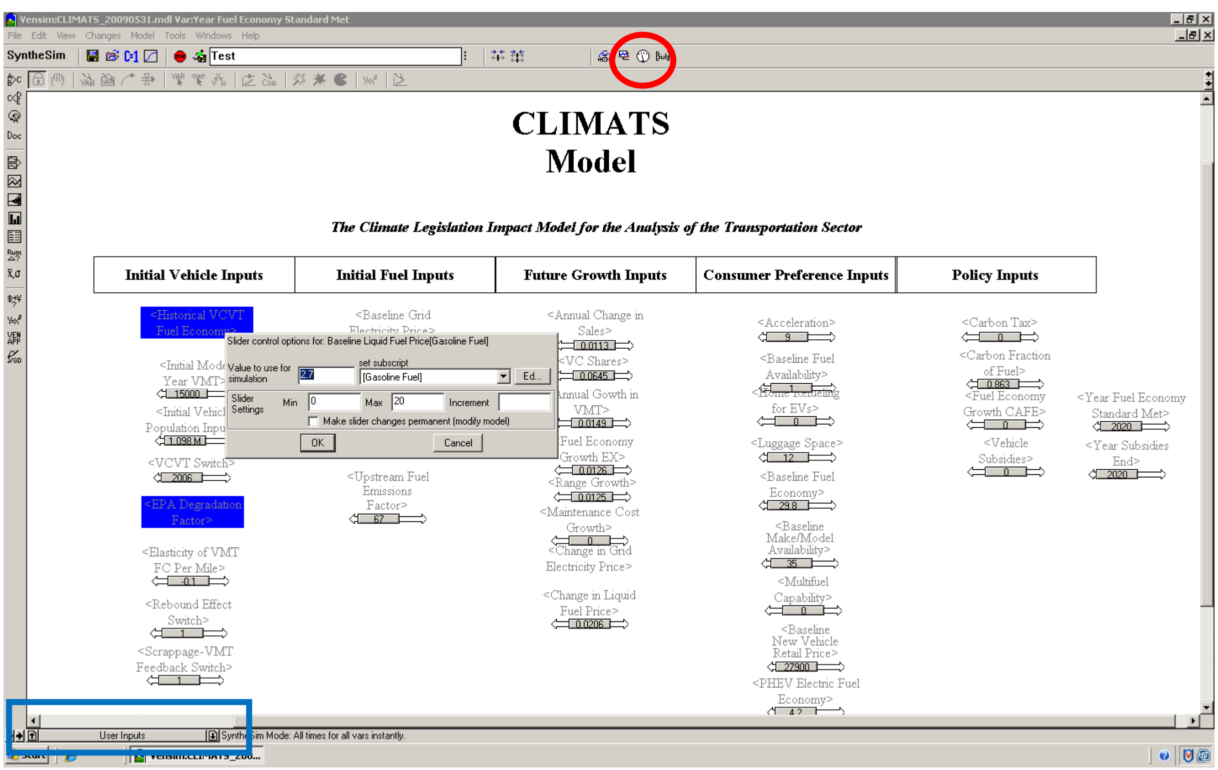

Figure 24 User input variable interface.

6. As each variable is changed, model results will change immediately. When all alterations are made, default result tables and graphs can be viewed by clicking *Control Panel* (circle) and navigating to the *Graphs* tab.

7. Users can exit the simulation by clicking the red *Stop* button on the toolbar. To navigate to the other two pages of the model, users can use the drop down menu in the bottom left corner of the page (rectangle).

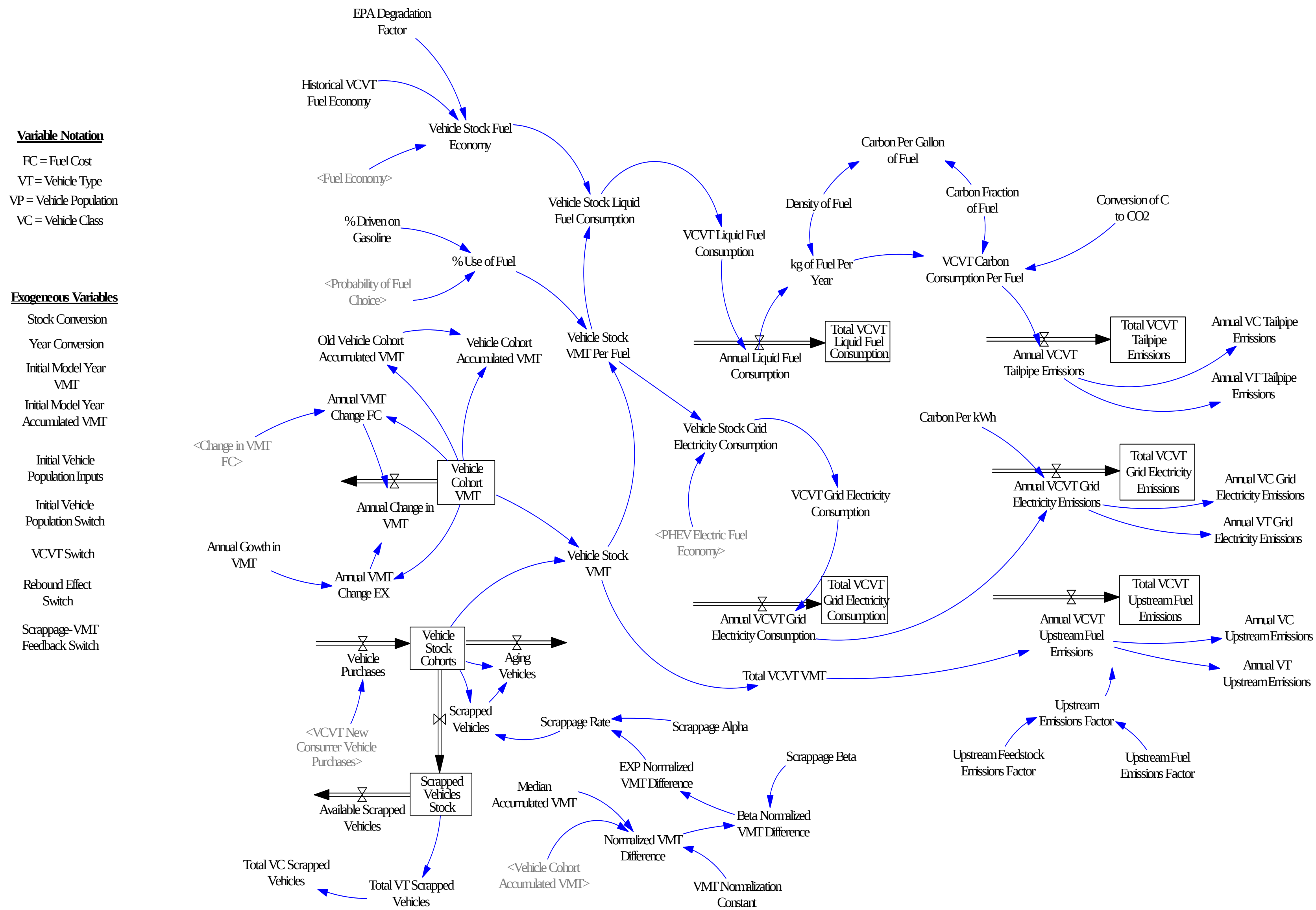

Figure 25 Cohort Submodel and Emissions Calculations Page.

4.4.4 Cohort Submodel and Emissions Calculations Page

The *Cohort Submodel and Emissions Calculations Page* includes all variables and dynamics used to simulate the vehicle population and is fully represented in Figure 25. A vehicles age, or vintage, is considered a *cohort* and is denoted by a series of stock and flow variables. CLIMATS considers vehicles up to 20 years old, therefore it contains 20 cohorts for each vehicle class and type contained in the variable *Vehicle Stock Cohorts* (cohorts are considered variable subscripts).

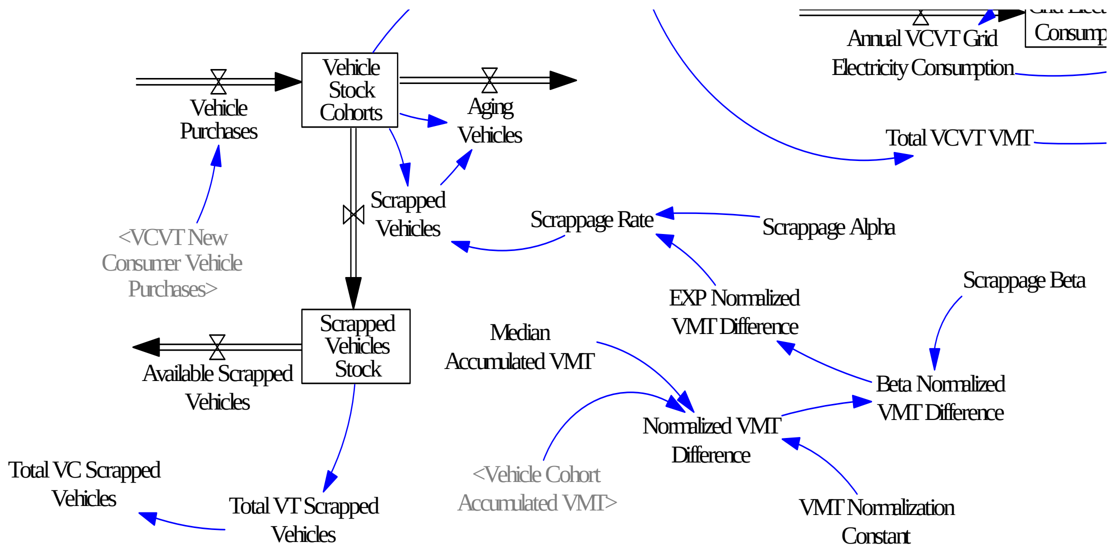

Figure 26 Vehicle population cohort model at the system level.

Figure 26 is a close up view of the variables representing the vehicle population. The flow variables *Vehicle Purchases* and *Scrapped Vehicles* represent vehicles entering and exiting the model. The *Aging Vehicles* flow variable simulates vehicles moving from cohort to cohort as each age. New purchases are calculated by the consumer choice submodel and vehicles can only exit the model through being scrapped.

4.4.4.1 Vehicle Scrappage and the Scrappage-VMT Feedback

There is considerable uncertainty about the scrappage rates of LDVs. A literature search found a number of methods and generalizations used to simulate scrapping vehicles.

The Transportation Energy Data Book (TEDB), a federal government publication of transportation sector related data, issues averaged scrappage rates given a vehicles age. TEDB calculates these values using a widely cited logistic function that estimates vehicle survival rates based on its age compared to the vehicle model's median value (Equation 1) (Bandivadekar et al., 2008; Davis and Diegal, 2007; Heywood et al., 2003).

$$1 - Survival\ Rate_t = \frac{1}{\alpha + e^{-\beta(t - t_o)}}$$

Where, t, is the vehicles age on a given year
t_0, is the median lifetime of the vehicles model
α, is a model parameter set to 1
β, is a growth parameter translating how fast vehicles are retired as they near t_0

Equation 1 Logistic function for vehicle scrappage rates.

The most recent TEDB reports cite an increase in the median lifetime of vehicles to 16.9 years for automobiles and 15.5 years for light duty trucks (from 13.7 and 15.2 years respectively), representing a long term shift in consumers keeping their vehicles longer as well as a dichotomy between vehicle classes (Bandivadekar et al., 2008; Davis and Diegal, 2007). The dynamics of this change are difficult to quantify.

Alan Greenspan and Darrel Cohen attempted to discern these dynamics by seperating scrappage into engineering and cyclical effects. Engineering scrappage is the result of the accumulation of wear and tear as a vehicle ages. Cyclical scrappage is due to macroeconomic effects (e.g. an economic recession), such as a consumer's income, the price of a new vehicle, and the cost of repairing a vehicle. Their findings suggest that engineering scrappage due to vehicle use over time represents over 90% of total scrappage (cyclical represents 10%) (Greenspan and Cohen, 1996).

This interplay between vehicle use (quantified as VMT) and scrappage will be called the *Scrappage-VMT Feedback* and it directly associates with the feedback discussed in Figure 17 of the CLD. Citing this feedback, Equation 1 is modified to depend on VMT instead of age.

$$1 - Survival\ Rate_t = \frac{1}{\alpha + e^{-\beta[\frac{(VMT_0 - VMT_t)}{VMT_N}]}}$$

Where, VMT_t, is the accumulated miles traveled for a vehicle on a given year
VMT_0, is the median accumulated VMT of the vehicles model
VMT_N, is a model parameter used to normalize the difference in VMT
α, is a model parameter set to 1
β, is a growth parameter translating how fast vehicles are retired as they near VMT_0

Equation 2 Logistic function for scrappage rate with VMT feedback.

The model parameters in Equation 2 were fitted to most closely match baseline TEDB scrappage values using Equation 1. Figure 27 illustrates the baseline scrappage rates of both Equation 1 (TEDB data) and Equation 2 (TEDB fitted parameters). To calculate baseline accumulated VMT data, annual VMT data published by TEDB was used (see *Appendix 5.2.3* for data) and VMT_N and Beta were estimated. It is assumed that vehicles are not scrapped within the first 5 years.

	Median Lifetime (*years*)	VMT_0 (*miles*)	VMT_N (*miles*)	Alpha(α)	Beta (β)
Automobiles	16.9	180000	8000	1	0.32
Trucks	15.5	220000	8000	1	0.25

Table 2 Baseline scrappage equation data.

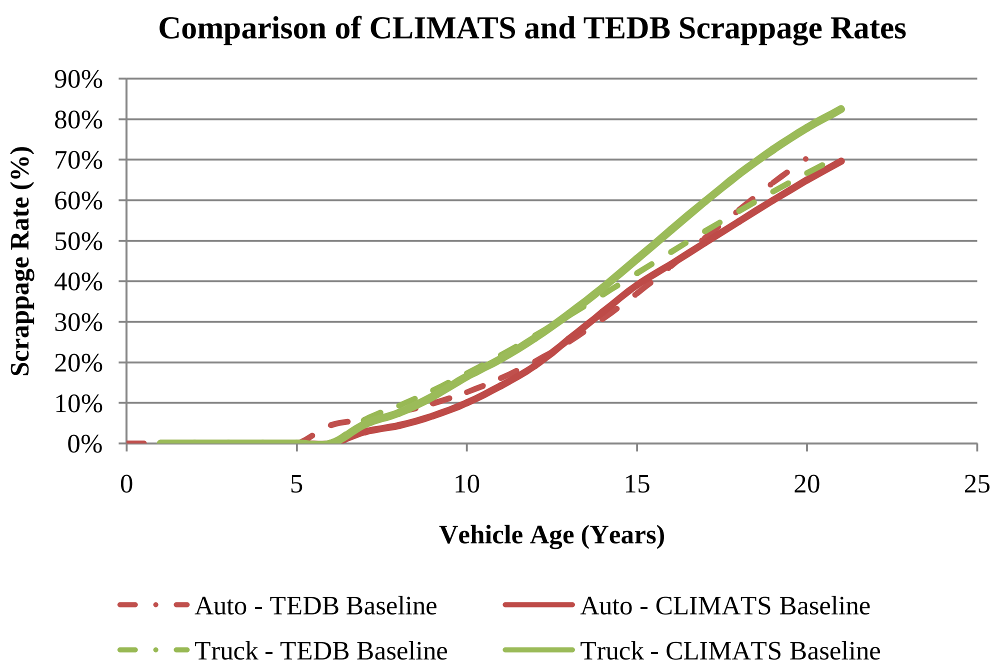

Figure 27 Comparison of scrappage rates using Equation 1 (TEDB) and Equation 2 (CLIMATS).

The results of Equation 2 fit reasonably well with published TEDB data. Given this, vehicle scrappage rates for the cohort submodel will be calculated using this method. Considering that there is no authoritative dataset on scrappage rates, validation can only be associative and workable at best, so the models sensitivity analysis will be used to assess the feedback's significance later in this study.

4.4.4.2 Vehicle Use, Fuel Consumption, and the Rebound Effect

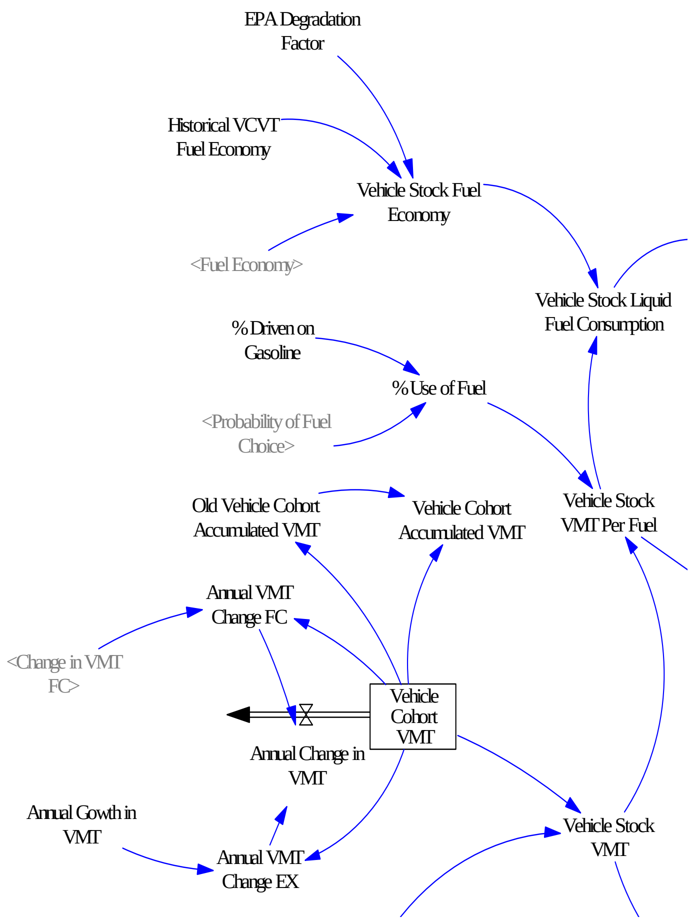

Figure 28 Vehicle use and fuel consumption variables.

Fuel consumption is dependent on the number of vehicles in the population in a given year (cohort submodel), how much each is driven, and each vehicle's fuel efficiency. Figure 28 captures these important variable interactions used in CLIMATS.

Vehicle fuel efficiency is dependent on historical values of the vehicles initialized in the cohort model (captured in *Historical VCVT Fuel Economy*) and the values set in the consumer choice submodel for new vehicles (represented in *Fuel Economy*). To account for the fact that the Environmental Protection Agency (EPA) does not adjust a vehicles sticker fuel efficiency rating for increased urban driving, congestive driving conditions, or increased highway speeds, degradation factors are used. The variable *EPA Degradation Factor* is set according to future values for automobiles and light trucks calculated by the EIA, which can be found in *Appendix 5.1.5*.

What fuel mix is used by each vehicle type is only important for PHEVs, HEVs, and FFVs. The percentage of FFVs driving either on gasoline or E85 (85% ethanol) is calculated in the consumer choice submodel (*Probability of Fuel Choice*). The percentage that electric based vehicles use gasoline is exogenously set due to a lack of quantitative data in the literature and is represented by *% Driven on Gasoline*.

The miles traveled by the vehicle population is an extension of the cohort submodel. Vehicle in each cohort is associated with a unique annual miles traveled value based on its class and type. This *Vehicle Cohort VMT* variable is dependent on an exogenous growth value inputted by the user (*Annual Growth in VMT)* and the change in vehicle travel caused by a change in the cost of driving, otherwise titled the *Rebound Effect*.

Long associated with many sources of consumer energy consumption, such as residential space heating, appliances, and transportation, the rebound effect feedback is cited as a partial offset in energy savings in response to economic reactions caused by improved energy efficiency (Greening et al., 2000; Small and Dender, 2007). In the case of transportation, a simple example would be an increase in travel due to a decrease in the cost of driving resulting from an increase in vehicle fuel efficiency. Such a feedback, articulated in Figure 13 of the CLD, is important to policy makers because if significant, price policies (e.g. carbon tax, vehicle subsidies, etc.) may be more effective than technology mandates, such as CAFE standards.

Based on the analysis commonly found in the literature and detailed by Small and Dender (2007) the rebound effect is said to be,

$$\Delta Annual\ Vehicle\ VMT = \varepsilon * \frac{\Delta Fuel\ Cost\ Per\ Mile}{Fuel\ Cost\ Per\ Mile}$$

Where, $\Delta Annual\ Vehicle\ VMT$ is represented as *Change in VMT FC* in the model and ε, is the elasticity of VMT to a change in fuel cost per mile

Equation 3 Rebound effect.

The rebound effect elasticity differs greatly in the literature depending on the data set used for analysis. Greene (1992) estimated the elasticity to be 5-15% using annual US transportation data from 1957-1989 (Greene, 1992). Extending the data into the 1990's found the effect to be roughly 11% (Jones, 1993) Small and Dender (2007) used an econometric model and extended data set (1966-2001), finding a much smaller elasticity of 4.5% in the short term. Given the uncertainty in the literature, the rebound effect will be set at 10%, which is widely used in other, similar modeling efforts, and a sensitivity analysis will be used to test resulting uncertainty (Bandivadekar and Heywood, 2004).

4.4.4.3 Emissions Calculations

CLIMATS calculates tailpipe emissions as well as upstream fuel emissions associated with the electricity grid, feedstock use, and fuel production. Results are organized for the entire LDV sector, vehicle classes, and vehicle types. The general fuel consumption equation can be stated as,

$$Fuel\ Consumption = \frac{(Number\ of\ Vehicles) * [(VMT\ per\ Vehicle) * (\%\ Driven\ on\ Fuel)]}{(Vehicles\ Fuel\ Efficiency)}$$

Equation 4 General vehicle fuel consumption.

which is calculated for all vehicle classes, types, and fuels in each cohort. GHG emissions are then calculated by multiplying consumption by fuel-specific coefficients outlined in *Appendix 5.1.1*.

4.4.5 Consumer Choice and Fuels Submodel Page

The *Consumer Choice and Fuels Submodel Page* combines both the simulation of consumers deciding what type of new vehicles to purchase (Figure 29) and those related to fuels (Figure 30). Due to the extensive computations related to each of the vehicle attributes modeled, many variables are listed on the right hand side of the page and are specifically organized.

All variables explicitly titled are the direct inputs of each vehicle's attributes. Variables prefixed with 'CE' represent utility function coefficients used in the decision making equations for each attribute. Variables prefixed with 'P' are internal calculations specific to each attribute for use in the utility equation. Variables prefixed with 'F' are vehicle attribute calculations specific to the fuel choice submodel. Vehicle price, range, and maintenance cost are calculated internally through the use of exogenous growth functions and initial year inputs, but not directly alterable every time step.

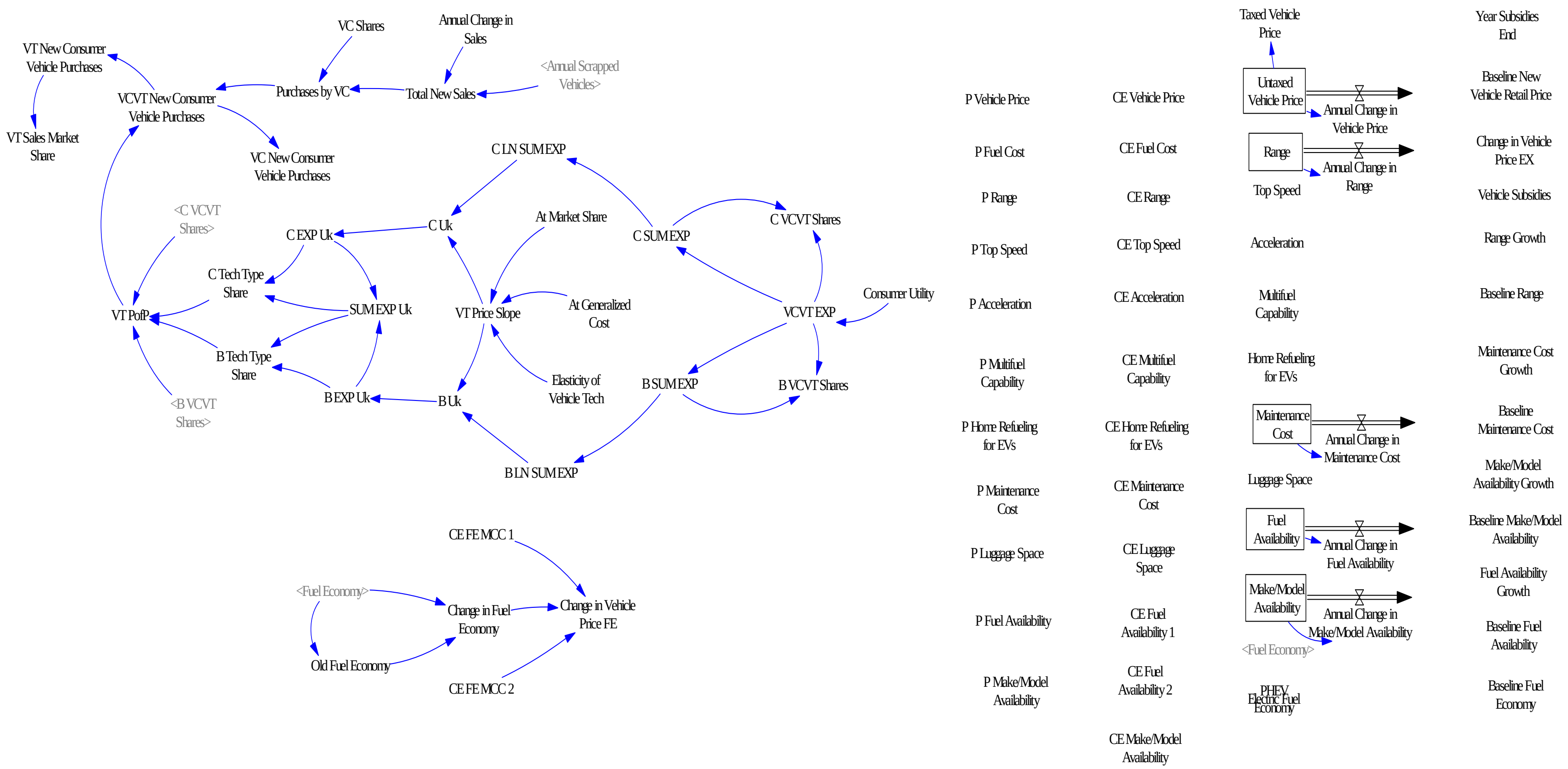

Figure 29 Consumer choice submodel.

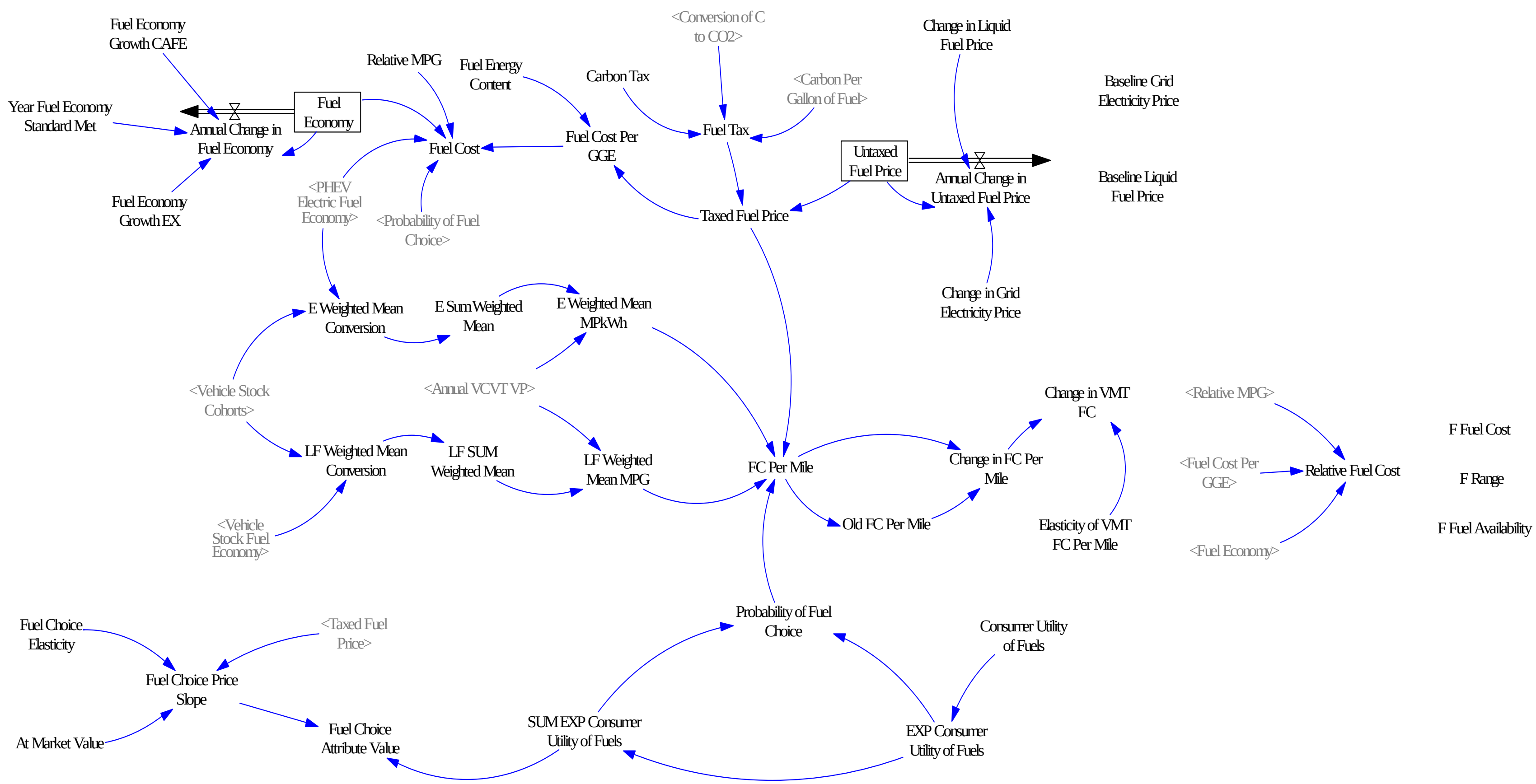

Figure 30 Fuels submodel.

4.4.5.1 Consumer Choice Submodel

Consumer decisions regarding new vehicle purchases can be thought of as being deterministic, meaning that there is no inherent randomness to the process of choosing. If one could observe all the factors that affected a consumer's decision, then one could predict accurately the alternative that would be chosen (Anderson et al., 1992). In reality, however, a researcher cannot observe all the attributes that affect the consumers' choice, leading to the use of both deterministic *and* stochastic variables in the utility function. Therefore, consumer utility generally modeled as,

$$U_i = u_i + \varepsilon_i, \text{ where } i = 1, \ldots., n\,,$$

where u_i is deterministic and represents utility from observable consumer choice attributes, ε_i is stochastic and represents utility from all unobservable consumer attributes, and i represents, in the case of this study, each vehicle class/fuel type combination. For example, given three vehicle attributes, the utility equation can be stated in the following form,

$$U_i = \beta_1 Attr1 + \beta_2 Attr2 + \beta_3 Attr3 + \varepsilon_i, \text{ where } i = 1, \ldots., n$$

Equation 5 General logit utility function.

where coefficients β_i are estimated using observed market share data for different vehicle types (Skerlos and Winebrake, 2007).

In general, given a set of vehicle type choices, the probability that a consumer chooses alternativeA_i,$(i = 1, \ldots., n)$, is generally given by,

$$P_A(A_i) = \Pr\,(U_i = \max_{j=1,\ldots,n} U_j), \text{ where } i = 1, \ldots., n.$$

Depending on the assumption about the distribution of the stochastic utility variable,ε_i different choice models are obtained. If the stochastic terms are assumed to be identically and independently distributed with double exponential distribution then a Multinomial Logit Model is calculated (Anderson et al., 1992). The probability function is then,

$$P_A(A_i) = \frac{\exp\,(u_i)}{\sum_{j=1}^{n} \exp\,(u_i)}, \text{ where } i = 1, \ldots., n,$$

Equation 6 General multi logit probability function.

Equation 6 gives the probability a consumer chooses a vehicle, based on its attributes, which is determined by the utility function given in Equation 5. Choosing what vehicle attributes to include is not a trivial process. The literature offers a wide variety and combination of attributes and utility coefficients using a multi logit method. A detailed discussion of different utility models can be found in Skerlos and Winebrake (2007). For this study the Greene Utility

Model was chosen due to its more extensive list of variables, organized in Table 3, and its prominent use in government reports and projects (EIA, 2008a; Greene, 2001).

Vehicle Attribute Variable	Units	User Input?
Acceleration	Seconds	Yes
Fuel Availability	Percentage	Yes
Fuel Cost	$ per gallon	No
Fuel Economy	Miles per gallon	Initial and Annual Change
Home Refueling Capabilities for Electric Vehicles	---	Yes
Luggage Space	Cubic feet	Yes
Maintenance Cost	2007 $	Initial and Annual Change
Make/Model Availability	---	Yes
Vehicle Price	2007 $	Initial and Annual Change
Range	Miles	Initial and Annual Change
Top Speed	Miles per hour	Yes

Table 3 Vehicle attributes used in consumer choice submodel.

Utility function coefficients deduced in Greene (2001) are used, based on vehicle class, and are presented in *Appendix 5.3.4* The decision making tree used in the Greene Utility functions are as follows, with decisions from top to bottom:

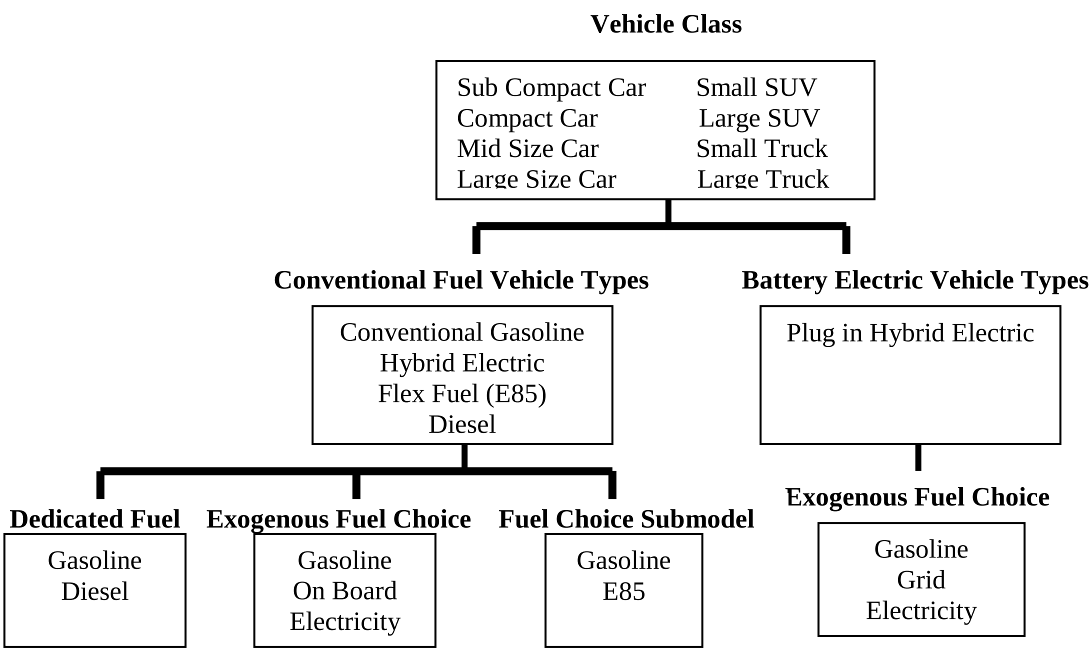

Figure 31 Consumer decision making sub model decision tree.

Using the tree it becomes easier to understand the variable logic in Figure 29. First, vehicle class shares (first level) are set exogenously through the variable *VC Shares*. Second, vehicle technology sets (second level) are calculated as two groups, conventional fuel (variables prefixed 'C') and battery electric (variables prefixed 'B'). Shares of individual vehicle technologies are then set within each technology set and fit within the class shares calculated initially. The probability of purchasing each vehicle class and type (*VT PofP*) is multiplied with the number of vehicles being sold during that time step, which is calculated as the sum of the annual number of scrapped vehicles (*Annual Scrapped Vehicles*) and an exogenous change in sales (*Annual Change in Sales*).

4.4.5.2 Fuel Economy Marginal Cost Curves

Though vehicle producer decision making is only captured in the model through the use of exogenous attribute inputs, policy specific feedbacks must still be simulated. The most important of these is the cost of new technology and the subsequent increase in vehicle retail price. As was previously discussed, forcing technological change in vehicles by setting fuel economy standards (CAFE), for example, lead to an additional cost to consumers.

Such a cost can be significant and alter consumer decision making. Recently proposed changes in CAFE standards for light duty cars and trucks of 35.5 miles per gallon by 2016 would increase the cost of new vehicles by an estimated average of $900 (Mufson, 2009). To capture this dynamic the choice of fuel economy influences the price of vehicles through marginal cost curves.

Using cost curves in this manner is an often cited method in the literature. Considering the vehicle classes included in CLIMATS, the cost curves first produced in a National Academies report on CAFE standards and later used by Greene et al. (2005), are used (Greene et al., 2005; NRC, 2002). Each curve is a quadratic equation, shown in Equation 7. Equation coefficients differ for each vehicle class and are listed in Table 4.

$$\Delta Vehicle\ Price = a_1 \left[\frac{FE_t - FE_{t-1}}{FE_{t-1}}\right] + a_2 \left[\frac{FE_t - FE_{t-1}}{FE_{t-1}}\right]^2$$

Where, FE = fuel economy.

Equation 7 Quadratic marginal cost curve of vehicle price vs. fuel economy.

Quadratic Marginal Cost Curve Coefficients		
Vehicle Class	Coefficient a_1	Coefficient a_2
Sub Compact Car	2599.3	3897.0
Compact Car	2619.7	3553.3
Mid Size Car	2799.3	2152.1
Large Car	2761.6	1690.3
Small SUV	2799.3	2152.1
Large SUV	2806.9	1656.4
Small Pickup Truck	2684.8	1870.9
Large Pickup Truck	2725.6	1857.4

Table 4 Fuel efficiency marginal cost curve equation coefficients by vehicle class.

Figure 32 further illustrates the average marginal cost curves for light duty cars and trucks based on general percent increases in fuel economy.

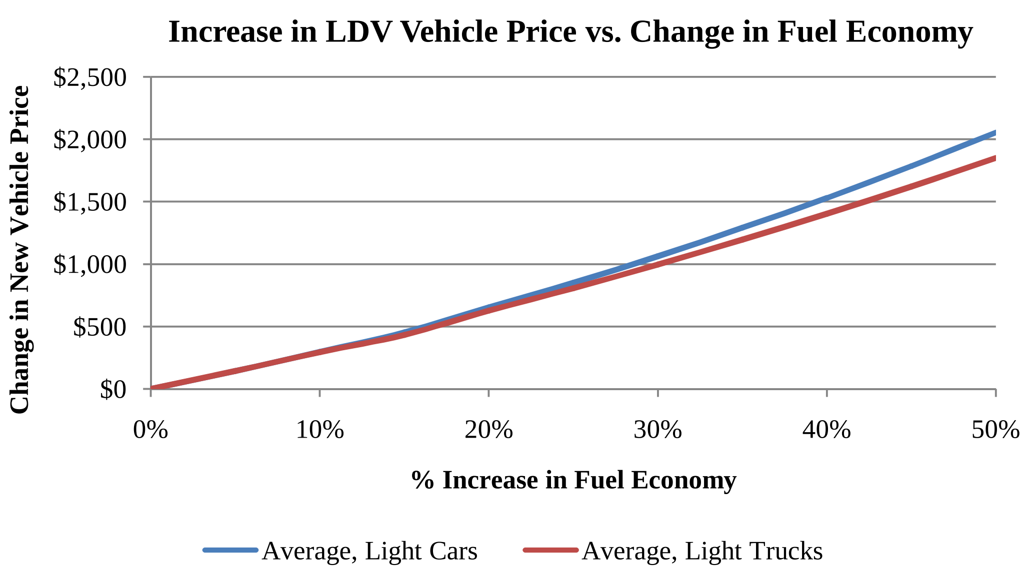

Figure 32 Average marginal cost curves for changes in fuel economy.

4.4.5.3 Fuels Submodel

The fuels submodel, shown in Figure 30, interacts with the consumer choice submodel and sets the price of liquid fuels and grid electricity, as well as the mix of fuels consumed by each vehicle and the cost of driving per mile for each vehicle class and type.

The price of gasoline, diesel, E85, and grid electricity are initialized exogenously and simulated through stock and flow variables, detailed in Figure 33. By allowing users to change the price of fuels on an annual basis instead of a submodel calculating a prediction, different fuel scenarios can be constructed (e.g. a lower price for gasoline). Also, flexibility is added by allowing users to set an exogenous *Carbon Tax*, which is additional to any annual change.

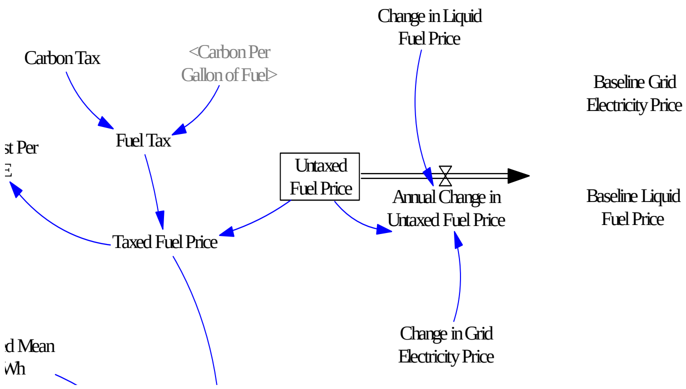

Figure 33 Fuel price variables.

The fuel choice submodel used to decide the mix of gasoline and E85 consumed by FFVs is based on the function used in Greene (2001),

$$U_{Fuel} = \beta_1(Fuel\ Cost\ Per\ Mile) + \beta_2(Range) + \beta_3(Fuel\ Availability)$$

Equation 8 Greene fuel choice utility equation.

The utility function coefficients are listed in *Appendix 5.3.4*. The probability a consumer will choose gasoline or E85 is calculated using the same functional form of Equation 6.

The cost of driving can then be established by multiplying the fuel cost per gallon by the inverse of the vehicle's fuel efficiency and weighting it by the mix of fuels used for each class and type. This fuel cost per mile calculation is then used as a deciding vehicle attribute in the consumer choice submodel and its annual change is used to calculate the magnitude of the rebound effect.

4.4.6 CLIMATS Model Validation and Sensitivity Analysis

Given the many dynamics and details included in CLIMATS, a thorough validation process is necessary to ensure that results are relatively accurate. With this in mind, CLIMATS simulations are run using Annual Energy Outlook (AEO) 2009 Update input data to compare with published results. AEO is produced annually by the Energy Information Administration (EIA) using the National Energy Modeling System (NEMS), which was discussed briefly in

Section 3. AEO forecast data is widely used in policy analysis, so it represents a good baseline to compare results with. See *Appendix 3* for the data tables and analysis.

Following validation, a sensitivity analysis is performed. Here, key exogenous variables are simulated over a wide range of variables to test the robustness of the model as well as provide information on the level of impact different variable have on scenario outcomes. See *Appendix 4* for the data tables and analysis.

5 Scenario Analysis

Now that CLIMATS has been reasonably validated and key exogenous variables have been analyzed, policy scenarios are simulated and discussed. To assess policy impact, scenarios are tested for whether interactive dynamics, such as policy synergies, resistance, or other unintended consequences, exist. The qualitative CLD presented previously in Figure 12 is used to provide insight into what feedback loops may be responsible for simulation results.

To fulfill these purposes, three often cited policies are studied: *Fuel Economy Standard, Carbon Tax, and New Vehicle Purchase Subsidies*. To analyze whether interactive dynamics exist when implemented in combination a three step approach is utilized.

<u>First, each policy is simulated individually using CLIMATS across a range of values within bounds discussed in the literature</u>, similar to the method used for conducting sensitivity analysis. Based on the results of the individual policy runs, *low*, *medium*, *and high* input values for each policy are chosen based on the impact each value has on total LDV emissions.

The approach of using different magnitudes of policies is not new. Climate policies have typically been described as being either core or complementary to achieving intended objectives, where a secondary policy "encourages" actions towards meeting environmental or energy goals (Sorrell, 2003). By testing the interaction of policies of different magnitudes, an assessment of whether an instrument is core to a piece of legislation or complimentary can be made, which is an important distinction decision makers must make.

Further, it is unknown whether *any* policy magnitude in combination will yield interactive effects and why. By testing combinations within low, medium, and high bounds, more specific and useful information about how aggressive or passive a policy must be to take advantage or heed interactive effects may result. This same information can be used, in combination with the CLD, to assess what feedbacks led to the results.

Choosing these values is based on the following criteria: proposed policy values from the literature, current policy values implemented in the US and an assessment of historical political feasibility. Both policy recommendations made in the literature and currently implemented US policies are used to provide high and low boundaries. Historic political feasibility is used to assess whether values are realistically capable of being implemented by US decision makers. For instance, providing a vehicle subsidy of $20,000 per PHEV will lead to a drastic increase in sales, but US policy makers would not be able to provide the significant funding necessary to implement such a policy.

<u>The second step is to use these low, medium, and high policy values to create the portfolio scenarios outlined in Table 5</u>. In total, 30 possible combinations exist. Results from the individual policy runs (Scenario 1-3) will be compared to portfolio results (Scenario 4-30) to assess whether synergies or resistance occur. Discussion of the portfolio scenarios will involve cases that led to significant results.

<u>The third step is to compare *all* possible combinations of policy portfolios within the bounds set in step 1</u>. Portfolio reductions are plotted as the percentage reduction of LDV emissions from the no policy case for each unique combination of the three policies. This visualization method illustrates unintended consequences not explicitly found in the individual scenario analysis and provides important insight to policy makers.

To be clear, this three step approach is important. The individual analysis must be discussed in detail so both synergy and resistance are explicitly calculated and a deeper understanding of *why* each occur. Discussing the plots of step 3 requires this understanding to assess the intricate, interactive effects that become apparent when illustrating model results in such a way.

Table 5 Policy portfolio scenario matrix. Black boxes indicate no scenarios. Gray boxes indicate repeat scenarios. Scenarios 1-3 are individual policy cases.

		Low Values			Medium Values			High Values		
		Fuel Economy Standard	**Carbon Tax**	**Vehicle Subsidies**	**Fuel Economy Standard**	**Carbon Tax**	**Vehicle Subsidies**	**Fuel Economy Standard**	**Carbon Tax**	**Vehicle Subsidies**
Low Values	**Fuel Economy Standard**									
	Carbon Tax	Scenario 4			Scenario 13			Scenario 22		
	Vehicle Subsidies	Scenario 5	Scenario 10		Scenario 14	Scenario 19		Scenario 23	Scenario 28	
Medium Values	**Fuel Economy Standard**									
	Carbon Tax	Scenario 6			Scenario 15			Scenario 24		
	Vehicle Subsidies	Scenario 7	Scenario 11		Scenario 16	Scenario 20		Scenario 25	Scenario 29	
High Values	**Fuel Economy Standard**									
	Carbon Tax	Scenario 8			Scenario 17			Scenario 26		
	Vehicle Subsidies	Scenario 9	Scenario 12		Scenario 18	Scenario 21		Scenario 27	Scenario 30	

5.1 Individual Policy Scenarios

Choosing what policies to include in the portfolio analysis is not a routine task. Implementing multiple policies should be coordinated to reach intended emission reductions at a greater impact than if each were implemented individually (Agras and Chapman, 1999; Supple, 2004). Ideally, the policies perturb different parts of the transportation system to generate a dynamic response.

Unfortunately, there isn't a consistent or unique method of characterizing transportation policies that would allow for a simple classification. One common, though broad system is to group policies as either supply (e.g. expand transportation capacity), regulation (e.g. command and control), or economic (Vieira et al., 2007). To explicitly tie policy instruments to the transportation sector, a combined approach will be used.

Table 6 combines this characterization, but detailed further by the vehicles lifecycle outline in Table 1. The three individual policies chosen for analysis represent different stages of the vehicle lifecycle as well as both market based options and command and control regulations (supply policies have been omitted). Characteristically, these policies effect different parts of the LDV system, so many of the feedbacks and dynamics qualitatively discussed in this thesis are directly important to scenario results. It can be assumed, then, that the policy scenarios proposed in Table 5 are unique and realistic.

Stage of Product Lifecycle	Command-and-Control	Market-based
Supply Chain Policies	• Regulate supply chain logistics	• Subsidize light weight material
Production Policies	• Fuel Economy standards	• Alternative fuel vehicle subsidies
Product Use Policies	• Carpooling lanes; restricted access to inner city roads	• Carbon Tax
End-of-Life (EOL) Policies	• Vehicle vintage recycling mandate	• Vehicle scrappage incentive program

Table 6 LDV GHG reduction policy examples based on vehicle lifecycle. Policies chosen for thesis highlighted.

5.1.1 Scenario 1: Individual Fuel Economy Standards

Fuel economy standards (FES), such as the US federal Corporate Average Fuel Economy standard (CAFE), is a regulation that requires vehicle manufactures to meet efficiency mandates within a certain time frame, in order to reduce fuel consumption or tailpipe emissions (NRC, 2002). In order to meet the imposed mandate, vehicle manufacturers typically must implement new engine technologies, light weight materials, decrease vehicle size, or produce alternative fuel vehicles. Within this context, a FES forces the implementation of new technology.

Historically, FESs has regulated light duty vehicle fuel economy since the 1970's, but with mixed results. Figure 10 captures the effects of CAFE standards on LDV fuel consumption since the policies inception in 1978. Due to a number of transportation system dynamics, such as a change in consumer driving habits and the inertia in overturning the vehicle population, FESs typically have not met intended policy goals.

Regardless, this policy choice is commonly discussed as a method for reducing transportation GHGs and fuel consumption. President Barack Obama recently increased CAFE standards for both light duty cars and trucks to 35.5 miles per gallon by 2016 (Mufson, 2009). The appropriate level to set efficiency standards in order to reduce tailpipe emissions is difficult to assess though.

There are numerous interactive feedbacks within the LDV system tied to fuel economy. Manufacturers must balance the cost of meeting those standards by choosing the most cost efficient mix of vehicle attributes that still meet consumer preferences. Consumers are expected to pay a higher price for more efficient vehicles, but pay less to travel over time, while also making purchasing decisions based on a suite of attributes (Table 3). CLIMATS does not endogenously calculate this important interplay (though research is ongoing), but the increased cost of FESs is captured in new vehicle retail price through the use of marginal cost curves.

Turnover of the LDV population takes time, so tailpipe reductions are delayed. CLIMATS includes feedbacks controlling the long term turnover of the LDV population, such as consumers scrapping their vehicles based on accumulated travel.

Traditional CAFE standards cannot be simulated by CLIMATS though, without a producer decision making submodel. Instead, a general fuel economy standard is simulated, where an annual change in efficiency is exogenously forced. It is assumed that the regulation is met by producers and that the mandate is met entirely by increasing the efficiency of new vehicles and not through the use of CAFE credits or penalties. Instead, this method assesses the emissions impact of FESs given the LDV population, driving habit, and purchasing feedbacks. While not entirely realistic, the impact of these feedbacks on policy results individually and in combination is important to understand.

For discussion in this thesis, it is assumed that the FES is met in 2020 equally by all classes (simulation begins in 2006), followed by no change in efficiency. Only conventional gasoline vehicles are subjected to the standard because it is assumed those vehicles are most directly affected by the regulation, though in reality all vehicles in a manufacturer's fleet are affected. Table 7 lists a range of CLIMATS results for increasingly more aggressive standards. The "No FES" scenario represents the AEO 2009 validation model simulation. For context, a 2%-3% scenario most closely represents the standards implemented by President Obama to meet the 35.5 miles per gallon mandate by 2016. Figure 34 illustrates the trend in fuel economy for each scenario over time.

Class Weighted New CGV Purchase Fuel Economy					
Policy Cases	2006 (Initial)	2010	2015	2020	2030
AEO 2009 Assumptions	26.7	28.0	29.5	31.2	34.9
1% Annual Increase	26.7	27.8	29.2	30.7	31.0
2% Annual Increase	26.7	28.9	32.0	35.3	36.0
3% Annual Increase	26.7	30.1	34.9	40.4	41.7
6% Annual Increase	26.7	33.8	45.2	60.5	64.1
9% Annual Increase	26.7	37.7	58.1	89.4	97.4

Table 7 Fuel economy standard scenario results for new conventional gasoline purchases.

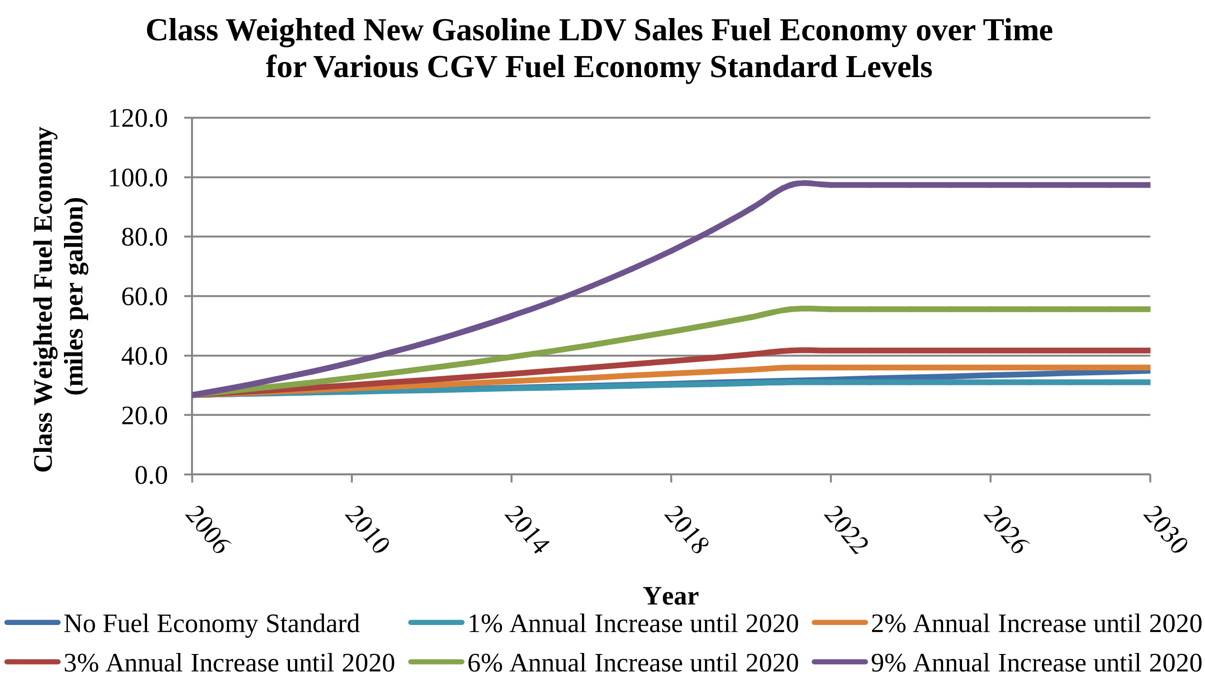

Figure 34 Scenario 1 Results: Class weighted fuel economy for new gasoline LDVs.

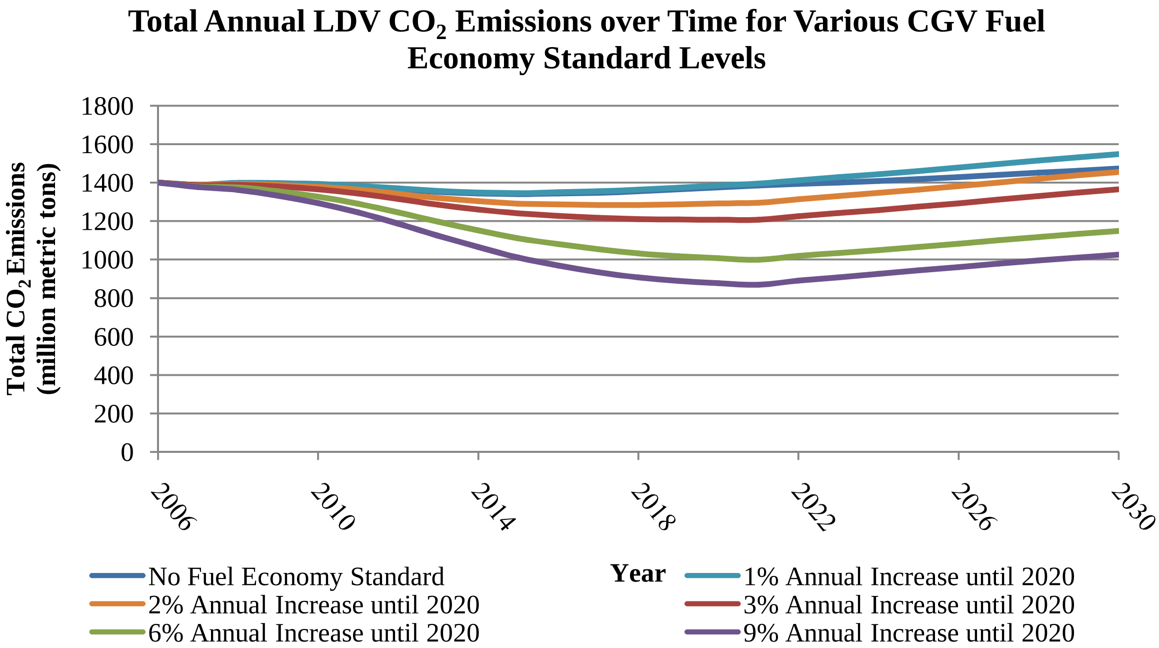

Figure 35 Scenario 1 Results: Total annual CO_2 emissions.

Breaking down the results provides important insight into feedback effects. Figure 35 illustrates the potential GHG reductions for each individual case. Notice the long term increasing trend in GHG emissions even with aggressive standards.

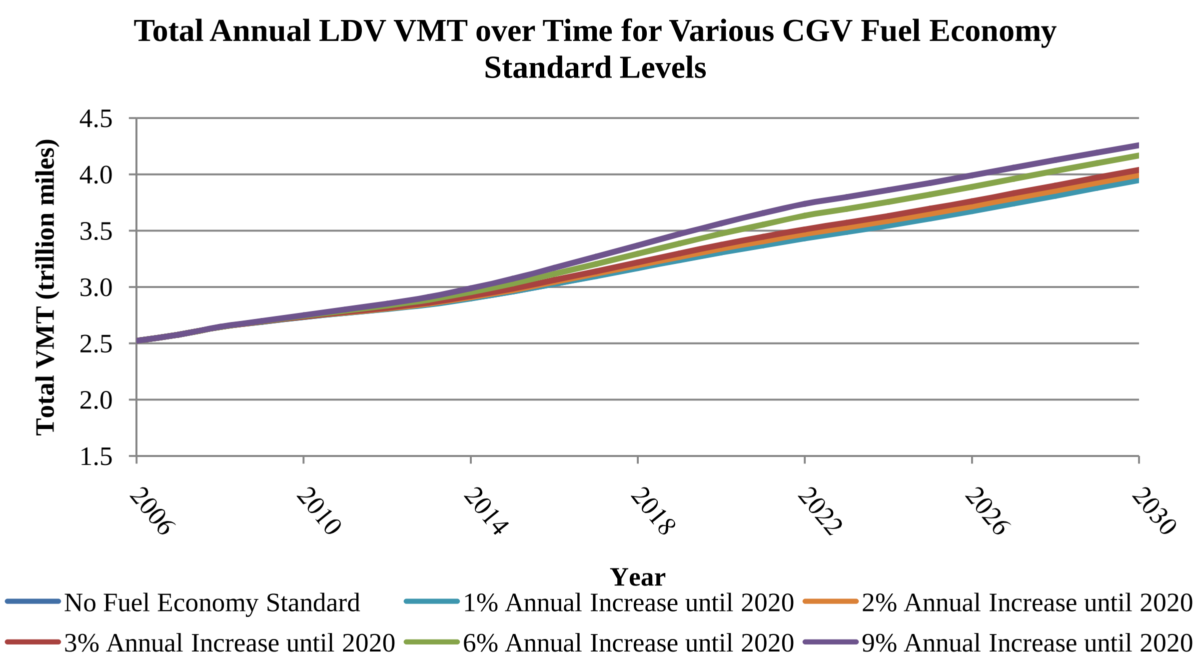

Figure 36 Scenario 1 Results: Total annual LDV VMT.

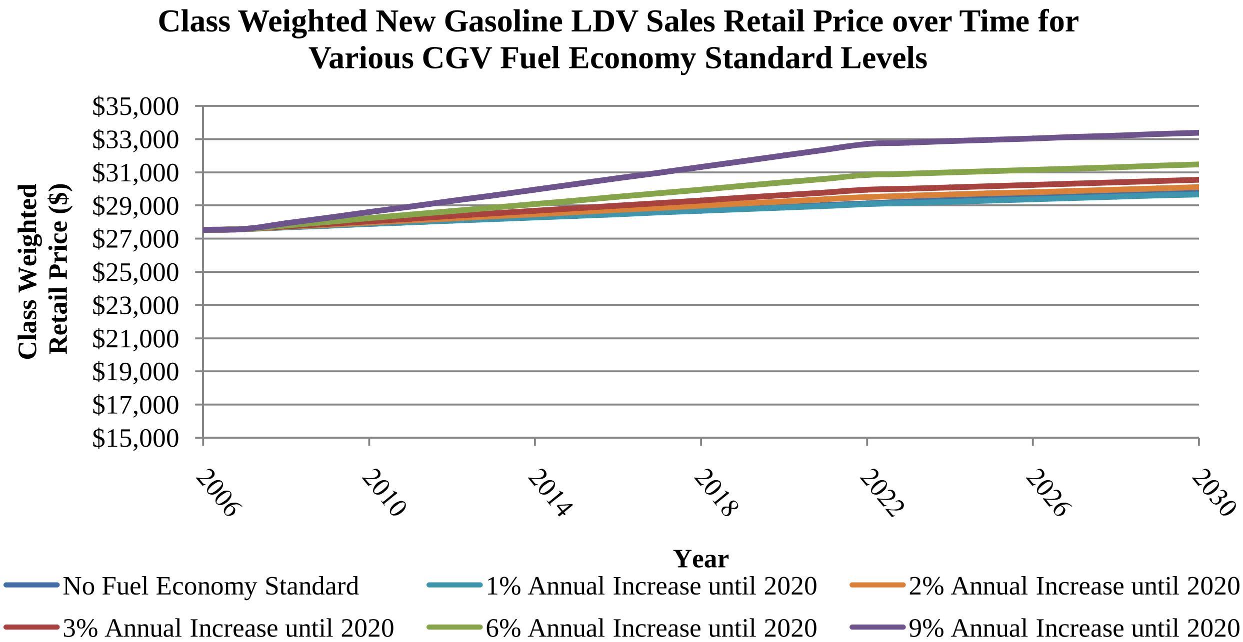

Figure 37 Scenario 1 Results: Class weighted new gasoline LDV retail price.

Reductions are most prominent in the short term, but as drivers travel more because of the decreased costs on a per mile basis (captured in the rebound effect) and by changing driving habits (e.g. number of trips, captured exogenously), emissions begin to creep upward. The effects of more aggressive FESs shift emissions downward compared to changing trends (e.g. the shape of the graph).

Figure 36 presents the trend in total population VMT over time for each scenario. The rebound effect results in the more aggressive scenarios resulting in higher VMT values. The cost of the FESs, passed on to consumers by manufacturers, also effected purchasing decisions.

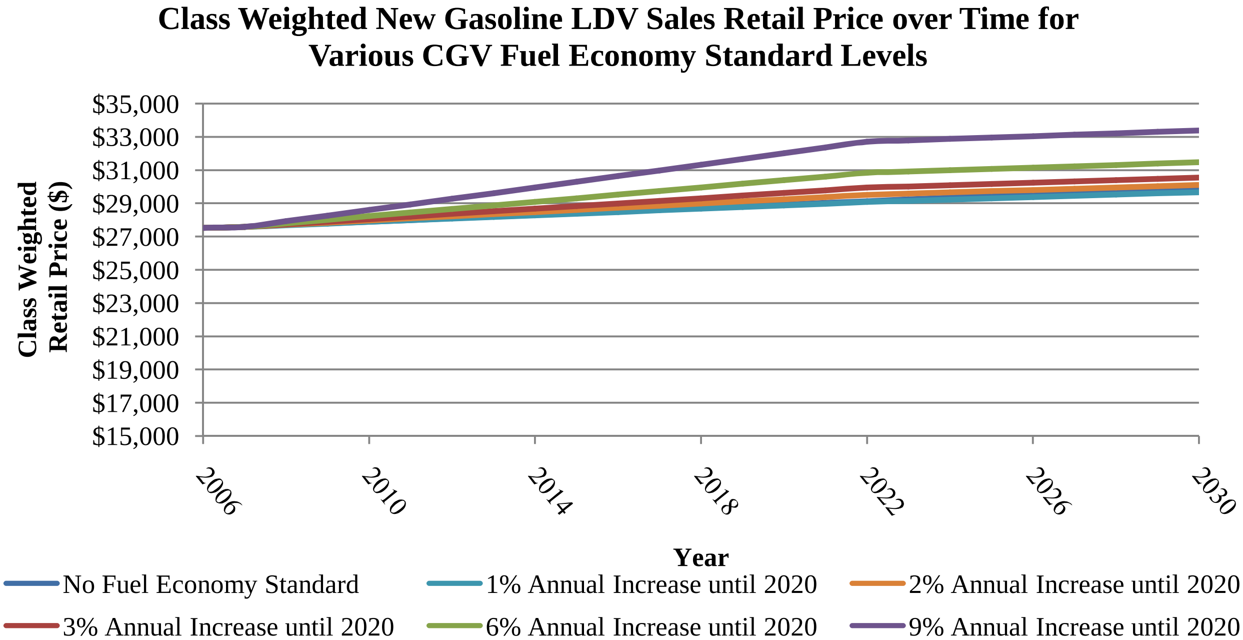

Figure 37 shows that the more aggressive the standard the higher the vehicle retail price, resulting in consumers to purchase less conventional gasoline vehicles sooner than less aggressive standards. Of note is the more rapid decrease in market share of conventional gasoline vehicles in the most aggressive, 9% annual increase case compared to the other scenarios (Figure 49).

In summary, FESs provide short and midterm GHG reductions as consumers purchase more efficient vehicles, but changing consumers driving habits and reaction to decreased travel costs may result in emissions rebounding in the long term. This long term trend is flexible though. Conventional gasoline vehicles constrained by federal regulation cost more to purchase, resulting in a greater number of consumers to purchase alternative fuel vehicles. This represents a shift away from gasoline, the most significant source of transportation emissions.

The weaknesses of FESs provide opportunities to test for synergies. Complementary policies that attend to the rebound in emissions due to changing driving habits could result in greater reductions. For instance, policies aimed at making alternative fuel vehicles more preferential to consumers may quicken the pace of market penetration, leading to possibly lower, sustained GHG levels.

Conversely, policy resistance is possible. Less aggressive standards may not result in a large enough increase in vehicle price, inhibiting the long term shift to alternative fuel vehicles. More aggressive standards may also out price those vehicles so much so that consumers decide to keep their older vehicles longer, creating inertia in turning over the LDV population.

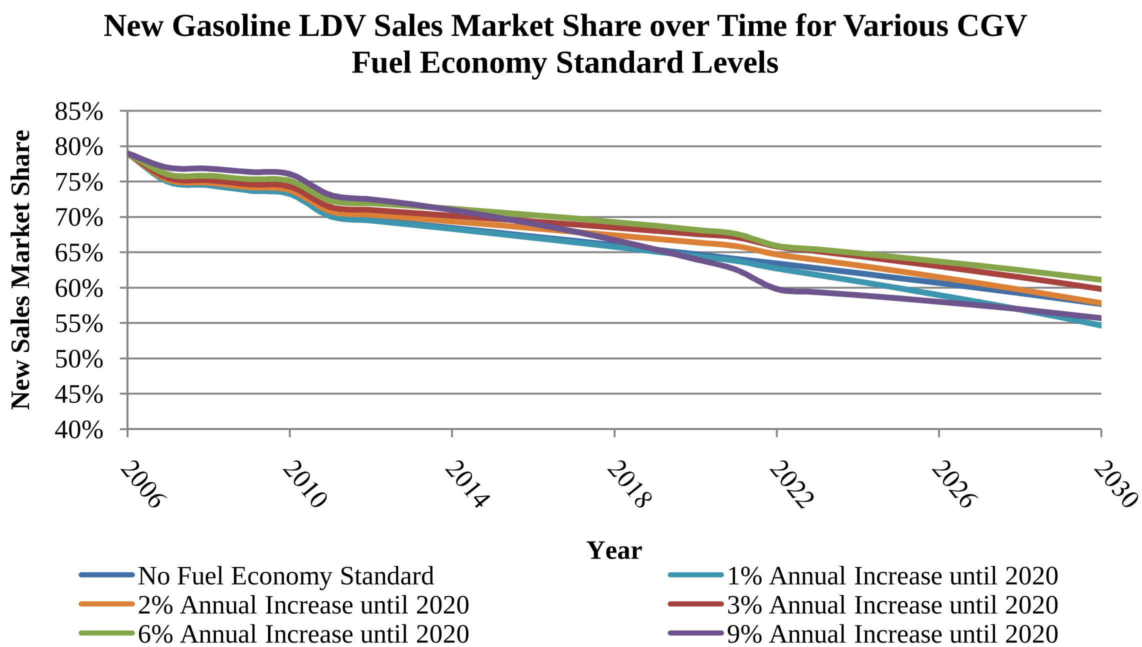

Figure 38 Scenario 1 Results: New gasoline LDV sales market share.

5.1.2 Scenario 2: Individual Carbon Tax

Another policy category, contrary to government command and control regulations like FESs, is market based mechanisms like a carbon tax. Under such a program, policy makers impose a per ton fee on CO_2 emissions that increase fossil fuel energy prices, changing consumer behaviors (e.g. driving inefficient vehicles) and providing an incentive for energy-related firms to move away from the more costly fossil fuel technologies.

A market based approach would affect each energy sector differently. Within the transportation sector a carbon tax can be implemented in two ways, either directed at upstream or downstream emissions. An upstream emissions program would apply to firms that produce, refine, and market fuels, taxing the fuels on a carbon content basis. A downstream emissions program would apply to the production of CO_2, requiring emissions produced by a firm to be tracked and tabulated. Due to the hardships in tracking emissions, the literature suggests an upstream carbon tax as the easiest to enforce and most likely to reduce emissions, therefore the most likely to be implemented (Nordhaus and Danish, 2003).

Setting the price of a ton of CO_2 (i.e. the carbon tax) is a widely debated field of research. The much publicized Stern Review calculated an optimal carbon tax of $314 per ton of carbon (roughly $1150 per ton CO_2) (Stern, 2007). The most recent estimates by William Nordhaus and his well cited RICE global economics model report an optimal tax of $70 per ton of carbon (roughly $257 per ton of CO_2) by 2050 (Nordhaus, 2007b).

At any price, a carbon tax is important to transportation emissions because it increases the cost of a gallon of gasoline (and any fuel that contains carbon). So, to reduce GHGs, the carbon tax must be great enough to elicit a consumer response to drive less, purchase a more fuel efficient vehicle, or purchase an alternative fuel vehicle. For this thesis, a range of CLIMATS runs are performed under the assumption that the increase in fuel cost is proportional to the carbon content of the fuel multiplied by the per ton CO_2 carbon tax.

Figure 39 narrates a telling story. A carbon tax below $100 per ton CO_2 (small insert graph) leads to a small, short term reduction in LDV emissions, but ultimately a midterm uptick mimicking the no tax scenario. Only large tax rates above $500 per ton CO_2 result in long term reductions.

Figure 40 illustrates the reason for this strong dichotomy in carbon tax results. Less aggressive tax rates lead to gasoline prices reaching roughly $5.00 per gallon by 2030, which is a significant cost to consumers, but not much different than the $4.00-$4.50 per gallon consumers were paying in 2008. Figure 41 details this more clearly by showing that the cost of traveling per mile, considering a tax below $100, does not provide a significant enough increase to consumers compared to no tax at all. Emission reductions only reflect a small decrease in driving and a slight shift to purchasing non-gasoline vehicles. Only a much more aggressive policy leads to meaningful results.

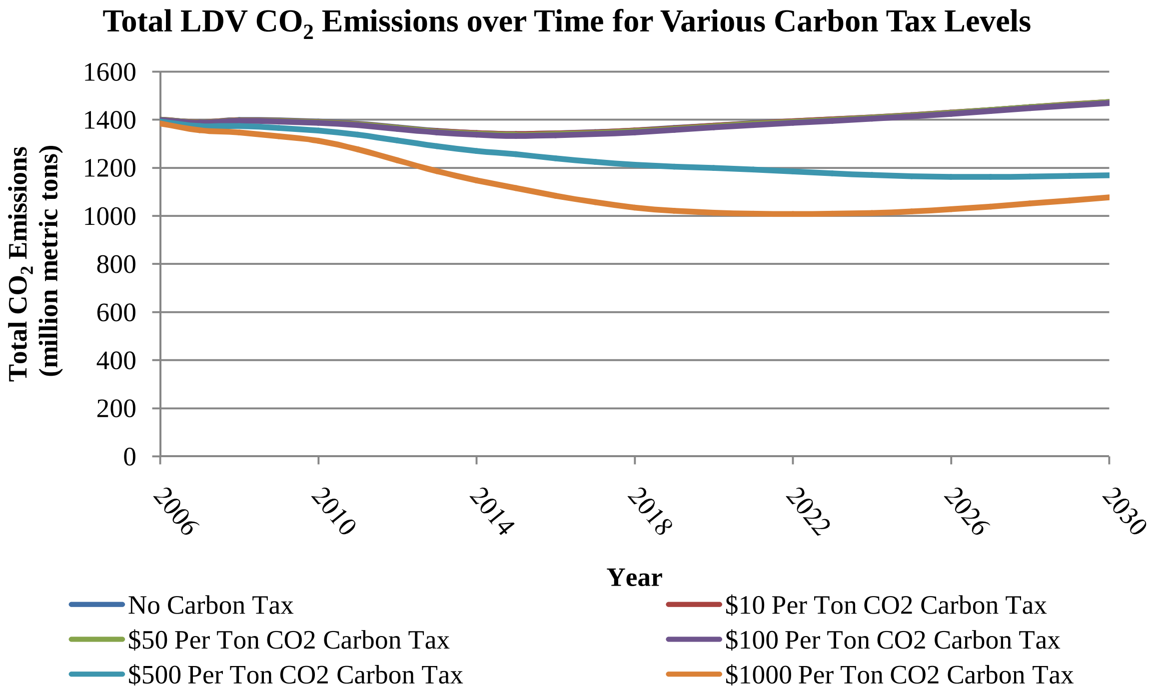

Figure 39 Scenario 2 Results: Total CO_2 emissions.

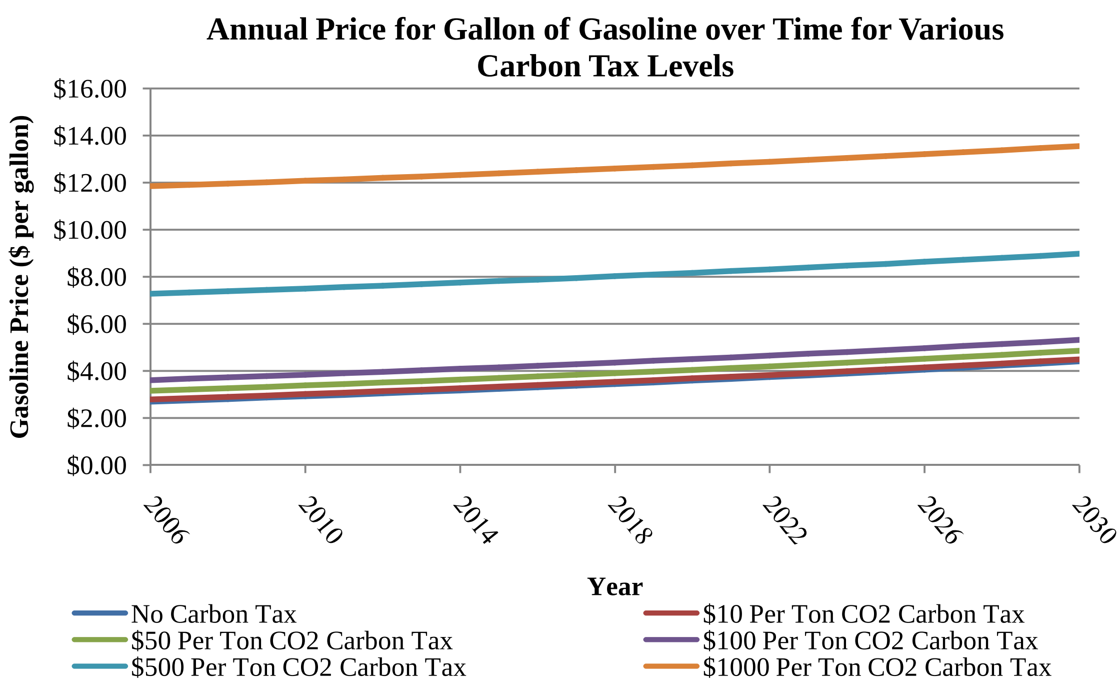

Figure 40 Scenario 2 Results: Annual price of conventional gasoline.

The more aggressive approaches ultimately lead to the long term GHG reductions because consumers begin drastically purchasing alternative fuel vehicles (Figure 42). Here, a carbon tax that nearly quadruples the current price of gasoline leads to the sales of gasoline vehicles to bottom out, stabilizing at just below 10% annual market share. A moderately aggressive $500 per ton CO_2 tax nearly reaches such a floor in gasoline vehicle sales, but much more gradually.

In all cases, consumer driving habits differ little. In fact, the relatively small impact of the rebound effect is clearly seen in Figure 43 and is greatly overshadowed by the exogenous growth factor that replicates consumers trending towards taking more vehicle trips.

In summary, a carbon tax has the potential to change consumer decision making, but only under more aggressive circumstances. A tax in line with the Stern Review, assuming only an interaction with fuel cost, leads to a 25%-30% reduction in emissions by 2030. Price levels

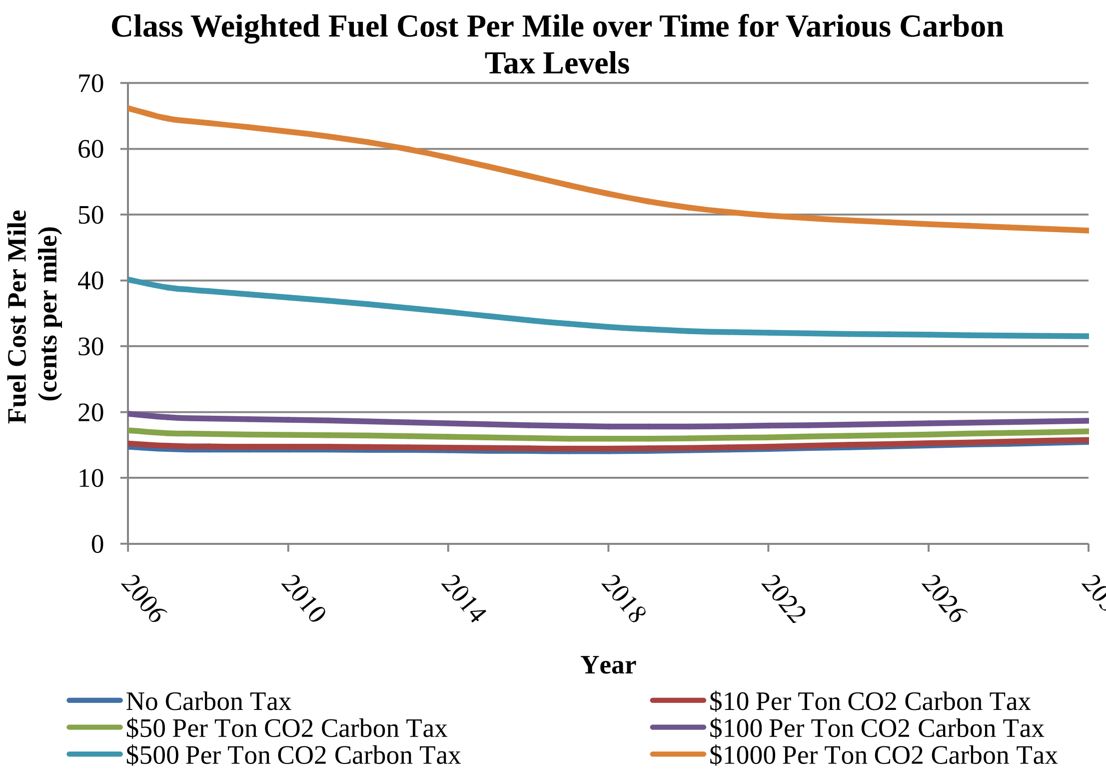

Figure 41 Scenario 2 Results: Class weighted fuel cost per mile.

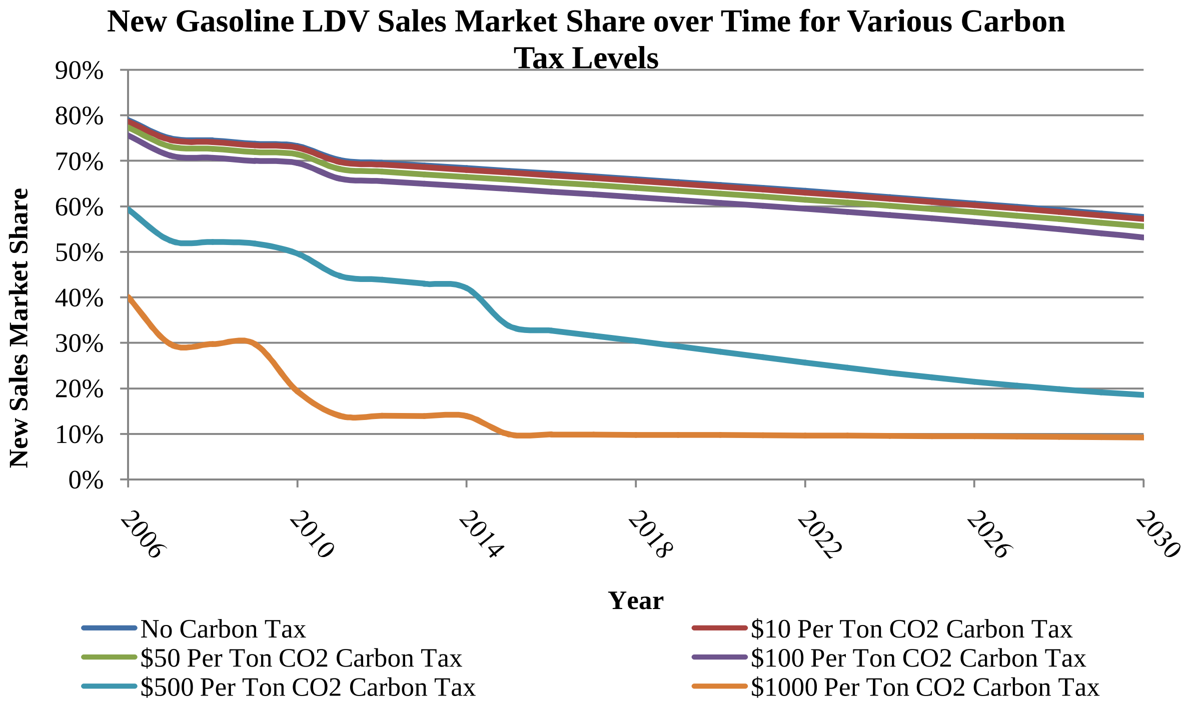

Figure 42 Scenario 2 Results: New gasoline LDV sales market share.

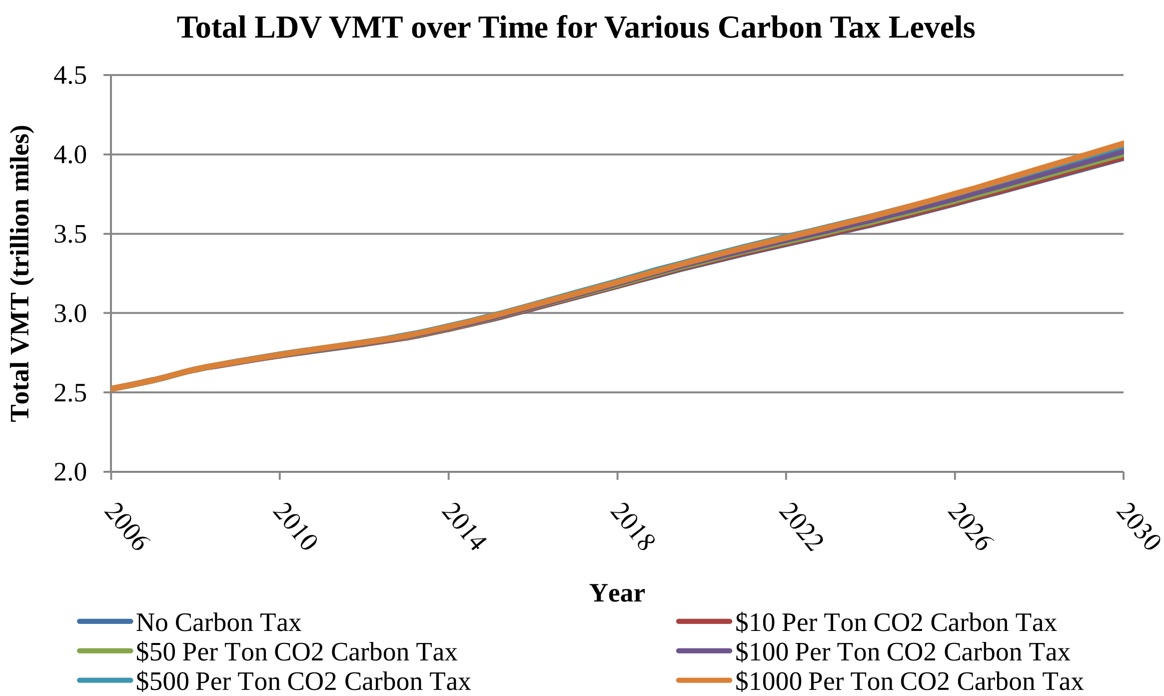

Figure 43 Scenario 2 Results: Total LDV VMT.

below $100 show signs of only small reductions due to traveling less, but little long term change in consumer purchasing decisions that would lead to more drastic cuts.

The weaknesses of a carbon tax provide opportunities to test for synergies. An increase in the cost of driving could play a role in making alternative fuel vehicles more palatable to consumers, improving the results of using a less aggressive tax level. Complementary policies could also be used to quicken the pace of alternative fuel vehicle market penetration under a moderately aggressive tax scenario.

Policy resistance is also possible. Note the upward trend in total emissions for the very aggressive $1000 per ton CO_2 scenario in Figure 39. The increase in emissions is due to the trend in purchasing PHEVs (50% sales by 2015), which still consumes gasoline when not using the electric battery and generates upstream fuel emissions due to electric grid consumption. Therefore, long term emission stabilization will require policies that nudge consumers towards purchasing other alternative fuel vehicles or electric grid decarbonization policies that lessen the upstream impacts of PHEV use.

5.1.3 Scenario 3: Individual New Vehicle Purchase Subsidies

The third policy category is new vehicle purchase subsidies. Most often implemented in the form of tax breaks or rebates, subsidies represent a second market-based approach that only interacts with consumer purchase decision making. Current US energy policy offers limited time tax breaks on hybrid electric vehicles of $4000 that are constrained by the number of vehicles sold by each manufacturer (EERE, 2009b).

Generally, subsidies are viewed as a means to push new technologies into the market at a greater rate by overcoming two burdens (Supple, 2004). First, new technologies are typically more costly. A key example is the $3,000 to $9,000 more consumers pay for a hybrid electric vehicle than if they purchased a conventional gasoline model. A tax break or rebate lessens the initial cost and increases sales. Second, the increased sales lead to a quicker adoption rate by the general public. Supple et al. (2004) discusses that consumers will trend to adopt new technologies through learning (e.g. seeing a neighbor with a new PHEV). Subsidies quicken the pace of this system feedback.

With the absence of a consumer learning feedback within CLIMATS, the simulations test the applicability of the magnitude of subsidies on the market penetration of different alternative fuel vehicle types. The scenarios assume that the subsidies expire after 2020. The effect of each case on total LDV emissions is presented.

Across all vehicle fuel types, the subsidy generates an emissions reduction during and shortly after the policy expires, followed by an increase as consumers switch back to gasoline vehicles. More importantly, the scenarios illustrate that not all alternative fuel vehicle subsidy is equal. PHEVs generate the most drastic emissions reduction (and also represent the most expensive vehicle pre subsidy) while FFVs result in a comparatively small decrease. Both HEVs and diesel vehicles fall between both extremes.

The implications of these results are few, but direct. Vehicle purchase subsidies, without assuming consumers "learn" and assimilate new technologies into the mainstream, must be consistently implemented over time to induce a response. When implemented, subsidies directly alter a vehicle's price, thus explicitly affecting an important vehicle attribute consumers take into account when making a purchase. All else being equal, once the subsidy is lifted, consumers will fall back to their original purchasing habits.

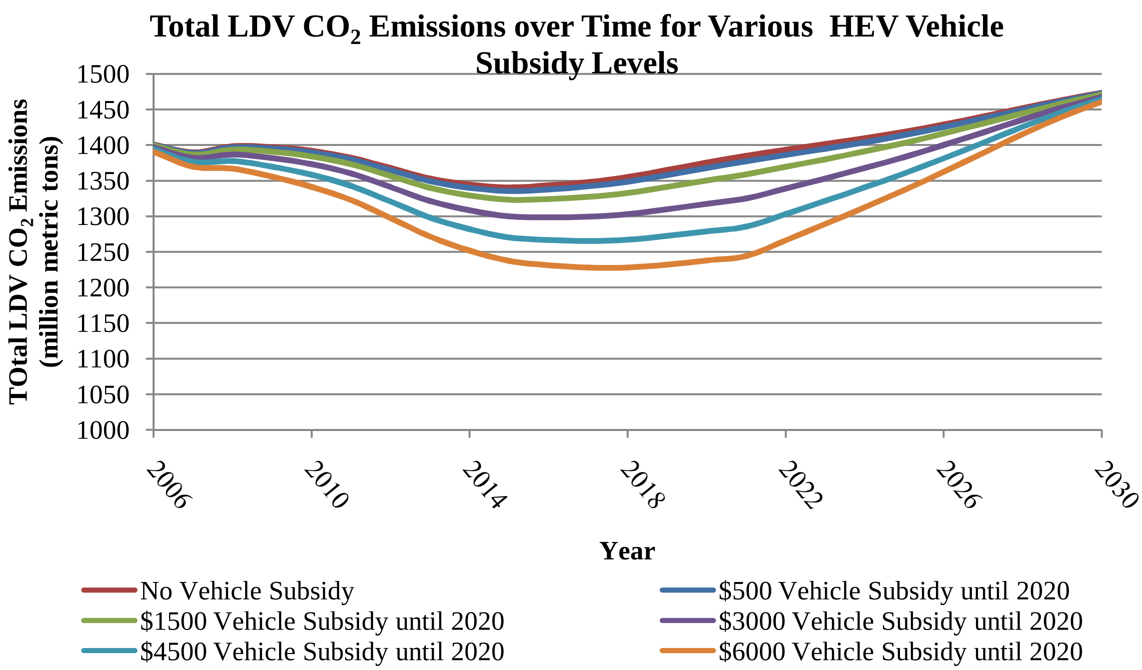

Figure 44 Scenario 3 Results: HEV subsidy emissions cases.

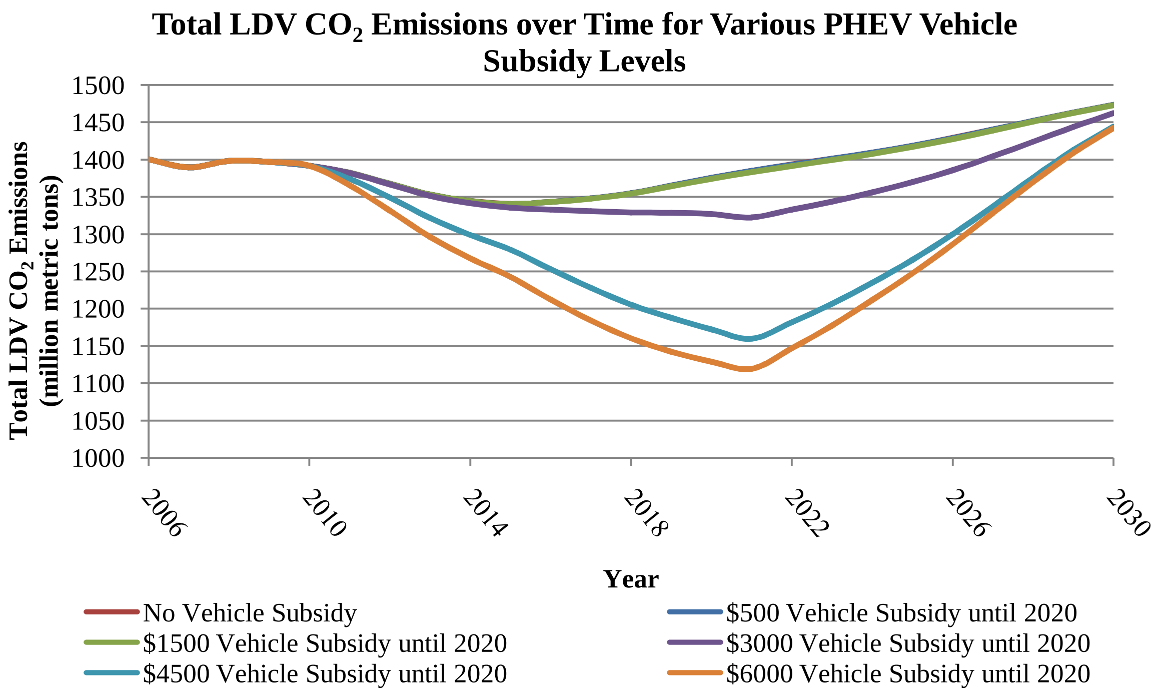

Figure 45 Scenario 3 Results: PHEV subsidy emissions cases.

Emission reductions are not equal among alternative fuel vehicles, given the same level of subsidy. PHEVs provide more “bang for the buck” by significantly reducing emissions, thus offer the better policy option to drive consumers to a low emissions vehicle (Figure 45). FFVs, which rely on consumers choosing to purchase E85, provide the least emissions reductions (Figure 46). Complementary policies that make gasoline less attractive to purchase and also increase the market penetration of E85 at fueling stations may drastically improve the viability of implementing FFV subsidies.

Figure 48 illustrates an additional scenario where subsidies were offered for multiple vehicle types, in this case HEVs and PHEVs. PHEVs decidedly were the better choice for consumers because even with equal price drops, HEVs still did not gain market share. The results of this case were most striking because emission reductions mimicked that of the individual PHEV subsidy case.

This case also provides insight into how the policy can be used most effectively. If multiple subsidies across different vehicle types are no different than individual vehicle type subsidies, policies can be used to target specific vehicles chosen as “better” technological options. For example, if the electric grid is slowly being decarbonized, it may be justifiable to incentivize other vehicle types that aren’t connected to the grid. Here, the policy acts like a *safety valve* to ensure that total US emissions are being reduced at the necessary trend and not gradually increasing.

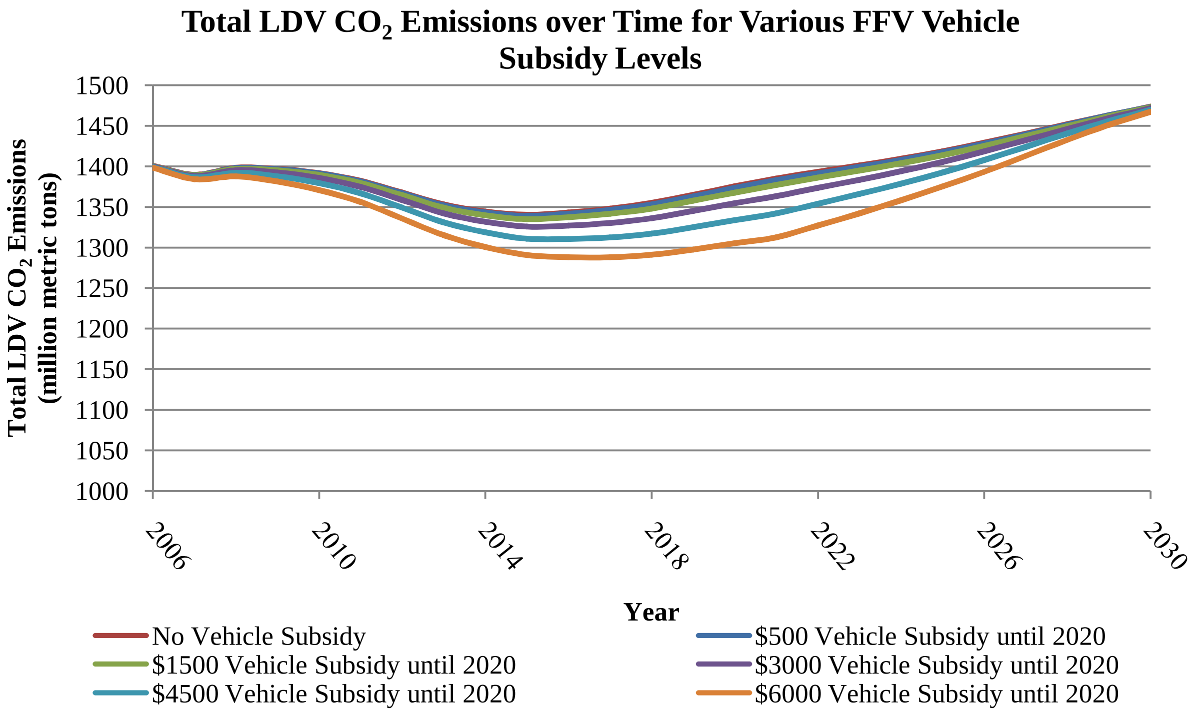

Figure 46 Scenario 3 Results: FFV subsidy emissions cases.

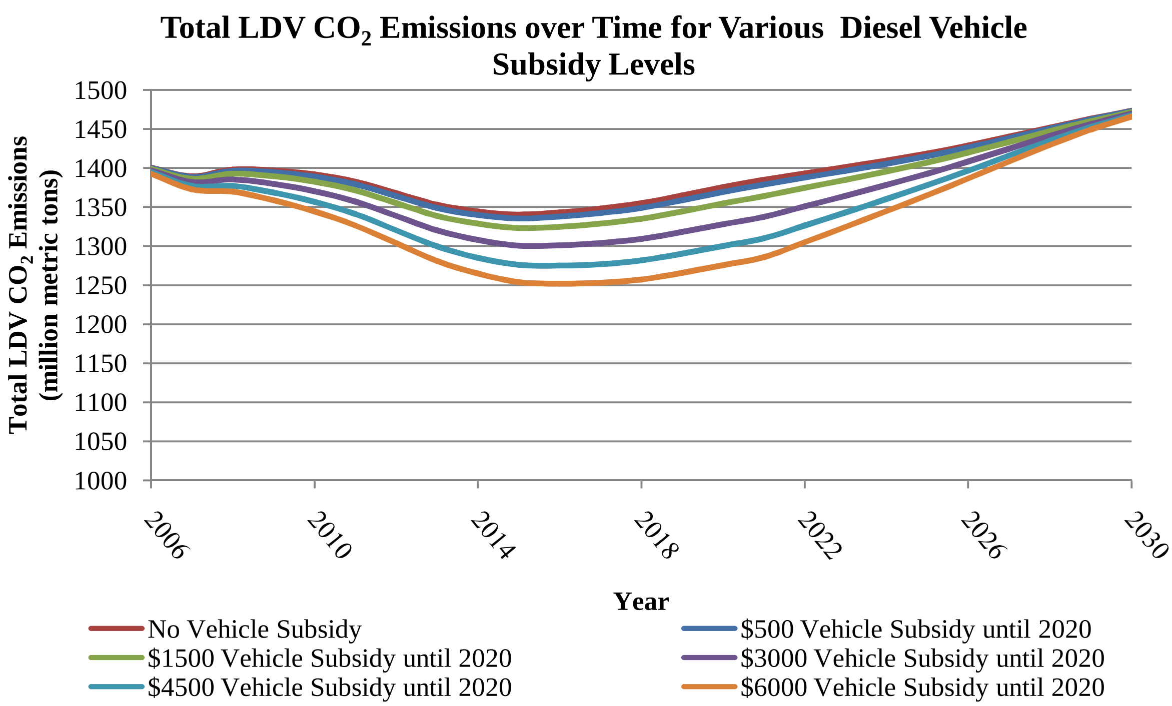

Figure 47 Scenario 3 Results: Diesel subsidy emissions cases.

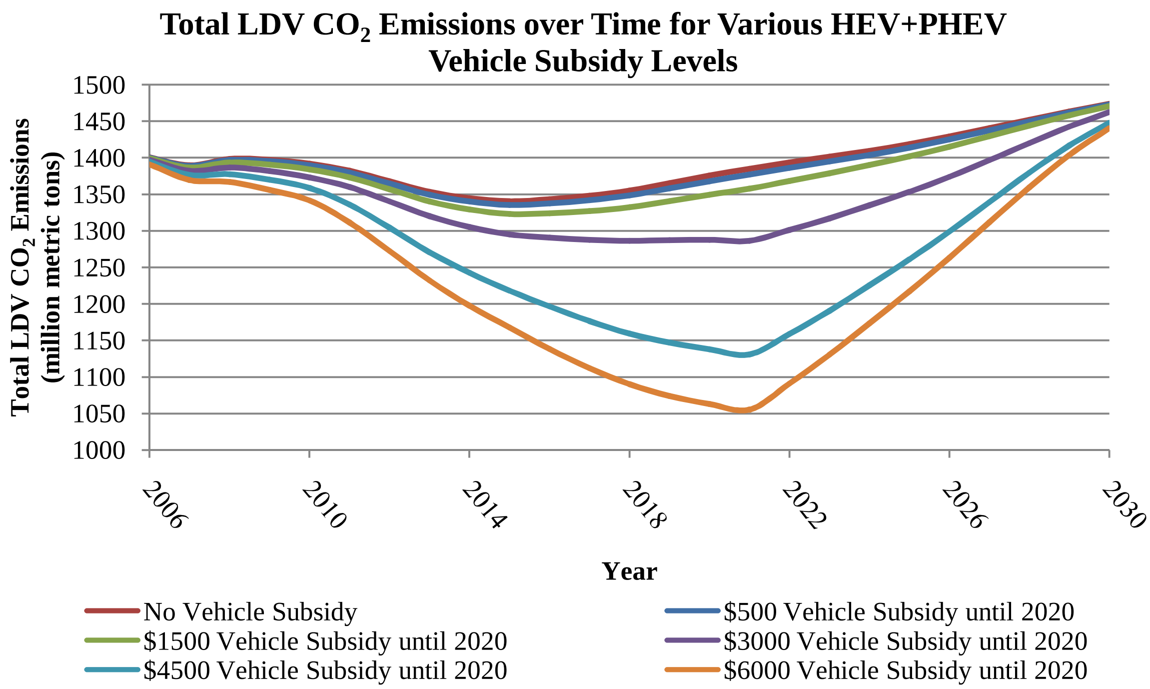

Figure 48 Scenario 3 Results: Electric vehicle subsidy emissions cases.

5.2 Policy Portfolio Scenarios

Using the results of the individual policy simulations, the portfolio scenarios in Table 5 are simulated. As previously discussed, proposed policy values from the literature, current US climate-energy policy, and political feasibility are used as decision rules to set low, medium, and high values. Table 8 outlines the values chosen.

Values Used in Portfolio Simulations				
Individual Policy Mechanism	Policy Description	Scenario Description		
		Low Values	Medium Values	High Values
Fuel Economy Standard	Only on CGVs. Increase until 2020, no increase thereafter	1% Annual	2% Annual	3% Annual
Carbon Tax	Implemented all years. Assumed costs only reflected in fuel price.	$10 Per Ton CO_2	$100 Per Ton CO_2	$500 Per Ton CO_2
Vehicle Subsidy	Only for PHEVs. Only in effect through 2020.	$500 Per Vehicle	$3000 Per Vehicle	$6000 Per Vehicle

Table 8 Policy values used in portfolio scenarios.

CLIMATS simulation results suggest an annual FES increase greater than 3% leads to 50+ miles per gallon new vehicles, which only currently exists for alternative fuel types. Present day US policy also dictates LDVs to reach 35.5 miles per gallon, representing what policy makers consider feasible. With this in mind, the medium value case is set at 2% (35 miles per gallon by 2020) and the high and low cases of 3% and 1% result in 2020 values of +/- 5 miles per gallon respectively.

Choosing carbon tax values is not as straight forward. The CLIMATS results showed that values less than \$100 per ton CO_2 did not lead to meaningful reductions. Only a tax that led to annual gasoline prices reaching \$7.00 to \$12.00 made an impact. Historically, though, such a government imposed increase in the price of gas has not been feasible. In the early 1990's, then President Bill Clinton endured a harsh political fight to increase the gas tax by just 4.3 cents a gallon (Krauthammer, 2009). Choosing a meaningful carbon tax that can overcome such political hurdles may not be possible.

An alternative path is taken then. To test whether a small carbon tax, in combination with other policies can lead to greater reductions, the low scenario is set at \$10 per ton CO_2. The \$100 per ton CO_2 case is set as the medium scenario based on it being a common value proposed in the literature (Nordhaus, 2007a). Though seemingly not politically feasible, a high carbon tax value of \$500 per ton CO_2 is set. While less than half the highest value proposed in the literature (Stern Review), such a high value may instigate system effects that the other cases may not.

To focus the analysis, the vehicle subsidy scenarios will only include PHEVs. Due to the individual PHEV subsidy scenarios leading to greater CO_2 reductions than the other vehicle types and their significance in the national debate on alternative fuel vehicles, it makes for more timely and interesting cases. Current US policy produces a range of subsidies that average \$4500 for alternative fuel vehicle purchases (EERE, 2009b). With that in mind, \$6000 is considered a more aggressive, high value case, which is also in line with currently discussed federal proposals (Obama and Biden, 2008). A low value of \$500 is considered in much the same way the low carbon tax case was set. This low value allows testing whether interactive effects exist, even with less aggressive policies. The medium value scenario represents a median case.

The results of the policy portfolio analysis will be presented in two ways. First, the results of all scenarios will be tabulated and tested for whether policy synergies or resistance exist. Scenarios that resulted in significant differences will be discussed using the CLD to describe feedback loops that led to the interactive effect. Second, all policy combinations are presented across a range of input values to discuss further unintended consequences that may occur.

5.2.1 Policy Portfolio Synergy and Resistance Analysis

Referring back to the beginning of the study, synergies are defined as an interaction of two or more policies that, when combined, achieve policy goals more successfully than would be achieved by each policy separately. On the other hand, resistance is defined as the opposite (Sterman, 2000). Generally, interaction effects are defined as the following,

$$\Delta Scenario = [LDV\ Emission\ Reductions_P - LDV\ Emission\ Reductions_B] - \sum_{S}^{n}[LDV\ Emission\ Reductions_S - LDV\ Emission\ Reductions_B]$$

Equation 9 Policy Interactive Effect Equation.

Where, $LDV\ Emission\ Reductions_P$ is the result of the portfolio scenario.
$LDV\ Emission\ Reductions_B$ is the result of the base case.
$LDV\ Emission\ Reductions_S$ is the result of the individual scenarios.
S is the policy scenario number, summed to the *n* number of policies in the portfolio.
$\Delta Scenario$ is the difference between the portfolio difference value and the sum of the individual difference scenarios.

The difference of the no policy case from each of the individual policy scenarios that construct the portfolio is summed. The difference of the base case from the corresponding portfolio scenario is then compared to this sum of the individual policy differences. Negative values of $\Delta Scenario$ are defined as policy resistance and positive values are defined as policy synergies.

Equation 9 is important to understand before continuing the analysis. It is entirely possible (and common in this study's results) for policy combinations to result in greater reductions than the individual policies, but *not* represent a policy synergy. A synergy, by definition, requires portfolio results to exceed the *sum* of both individual policies results. If portfolios are less than the sum, but greater than the impact of each individual policy, the combination is considered policy resistant because there is decreasing marginal reductions. Such portfolios can also be considered *complementary, but deficient* because greater reductions are met, but not optimized due to system feedbacks.

With that said results of the 27 portfolio scenarios are presented in Table 9. Total LDV emission values from 2020 are compared (initial simulation time of 2006) because both the FES and subsidy policies were simulated to end that year. Due to CLIMATS not including a consumer learning sub model, it is necessary to use a time step that evaluates both policies working in tandem. Further, because PHEVs enter the model in 2011 to replicate real world conditions, 2020 represents a significant period of time for the vehicles to enter the vehicle population.

Table 9 Policy portfolio scenario analysis results (colors for emphasis).

Scenario Number	Scenario Description *Note:* *FES = Fuel Economy Standard* *CT = Carbon Tax* *VS = PHEV Subsidy*	Individual Policies 2020 Total LDV Emissions *(million metric tons CO2)*			Policy Portfolios 2020 Total LDV Emissions *(million metric tons CO2)*		Portfolio – Σ[Ind. Policies] *(million metric tons CO2)*	% Difference
		Values	Diff. from Base Case	Sum	Values	Diff. from Base Case		
AEO 2009 Update Base Case	See AEO 2009 Update Validation	1385.5	---	---	---	---	---	---
Scenario 4	Low FES Low CT	1385.3 1375.4	0.2 10.1	10.3	1384.8	0.7	-9.59	-93.38%
Scenario 5	Low FES Low VS	1385.3 1375.4	0.2 10.1	10.3	1385.2	0.3	-10.07	-97.39%
Scenario 6	Low FES Medium CT	1385.3 1367.9	0.2 17.6	17.8	1376.8	8.7	-9.06	-50.98%
Scenario 7	Low FES Medium VS	1385.3 1326.9	0.2 58.6	58.8	1335.4	50.1	-8.65	-14.71%
Scenario 8	Low FES High CT	1385.3 1198.7	0.2 186.8	187.0	1200.2	185.3	-1.69	-0.90%
Scenario 9	Low FES High VS	1385.3 1128.7	0.2 256.8	257.0	1136.0	249.5	-7.43	-2.89%
Scenario 10	Low CT Low VS	1375.4 1375.4	10.1 10.1	20.2	1374.9	10.6	-9.66	-47.80%
Scenario 11	Low CT Medium VS	1375.4 1326.9	10.1 58.6	68.7	1319.3	66.2	-2.43	-3.54%
Scenario 12	Low CT High VS	1375.4 1128.7	10.1 256.8	266.8	1128.1	257.4	-9.42	-3.53%
Scenario 13	Medium FES Low CT	1292.2 1375.4	93.3 10.1	103.4	1292.4	93.1	-10.29	-9.95%
Scenario 14	Medium FES Low VS	1292.2 1375.4	93.3 10.1	103.5	1292.1	93.4	-10.09	-9.75%
Scenario 15	Medium FES Medium CT	1292.2 1367.9	93.3 17.6	110.9	1291.3	94.2	-16.71	-15.07%
Scenario 16	Medium FES Medium VS	1292.2 1326.9	93.3 58.6	151.9	1254.2	131.3	-20.62	-13.57%
Scenario 17	Medium FES High CT	1292.2 1198.7	93.3 186.8	280.1	1184.1	201.4	-78.77	-28.12%

Scenario Number	Scenario Description *Note:* *FES = Fuel Economy Standard* *CT = Carbon Tax* *VS = PHEV Subsidy*	Individual Policies 2020 Total LDV Emissions *(million metric tons CO2)*			Policy Portfolios 2020 Total LDV Emissions *(million metric tons CO2)*		Portfolio – Σ[Ind. Policies] *(million metric tons CO2)*	% Difference
		Values	Diff. from Base Case	Sum	Values	Diff. from Base Case		
Scenario 18	Medium FES High VS	1292.2 1128	93.3 256.8	350.1	1075.6	309.9	-40.15	-11.47%
Scenario 19	Medium CT Low VS	1367.9 1375.4	17.6 10.1	27.7	1367.3	18.2	-9.55	-34.46%
Scenario 20	Medium CT Medium VS	1367.9 1326.9	17.6 58.6	76.2	1236.6	148.9	72.71	95.47%
Scenario 21	Medium CT High VS	1367.9 1128.7	17.6 256.8	274.3	1121.7	263.8	-10.54	-3.84%
Scenario 22	High FES Low CT	1208.0 1375.4	177.5 10.1	187.6	1208.6	176.9	-10.69	-5.70%
Scenario 23	High FES Low VS	1208.0 1375.4	177.5 10.1	187.7	1207.9	177.6	-10.1	-5.38%
Scenario 24	High FES Medium CT	1208.0 1367.9	177.5 17.6	195.1	1211.6	173.9	-21.18	-10.86%
Scenario 25	High FES Medium VS	1208.0 1326.9	177.5 58.6	236.1	1177.5	208.0	-28.12	-11.91%
Scenario 26	High FES High CT	1208.0 1198.7	177.5 186.8	364.3	1152.7	232.8	-131.59	-36.12%
Scenario 27	High FES High VS	1208.0 1128.7	177.5 256.8	434.3	1020.6	364.9	-69.38	-15.98%
Scenario 28	High CT Low VS	1198.7 1375.4	186.8 10.1	197.0	1150.1	235.4	38.42	19.51%
Scenario 29	High CT Medium VS	1198.7 1326.9	186.8 58.6	245.4	1073.1	312.4	67.03	27.31%
Scenario 30	High CT High VS	1198.7 1128.7	186.8 256.8	443.6	1072.7	312.8	-130.79	-29.49%

5.2.1.1 Policy Resistance

LDV system feedback loops interacted to cause two groups of portfolios – carbon tax/fuel economy standard and PHEV subsidy/ fuel economy standard – to result in policy resistance. Depending on the magnitude of each policy, the portfolios resulted in 1% to 98% fewer emissions than the sum of the reductions of the individually implemented policy. Using the CLD and CLIMATS simulation data, the feedback loops responsible are isolated. Blue circles in the CLD represent variables perturbed or directly important to GHG emissions.

For all carbon tax/fuel economy standard scenarios (Scenarios 4, 6, 8, 13, 15, 17, 22, 24, and 26), Figure 51 illustrates that the balancing loop *B7* inhibits the cost of driving gasoline vehicles from increasing over time. Individually, the carbon tax (orange box) causes the price of gasoline (*Fuel Price*) and therefore the cost of driving (*Cost/*Mile) to increase. This decreases the amount of annual travel, reducing vehicle operation emissions.

The opposite can be said of the FES policy. A government imposed increase in fuel economy (green box), leads to a decrease in *Cost/mile* (connected blue circle). Through the same feedback loop, this decrease in the cost of driving increases the amount of travel through the rebound effect and increases emissions, depending on the magnitude of the policy.

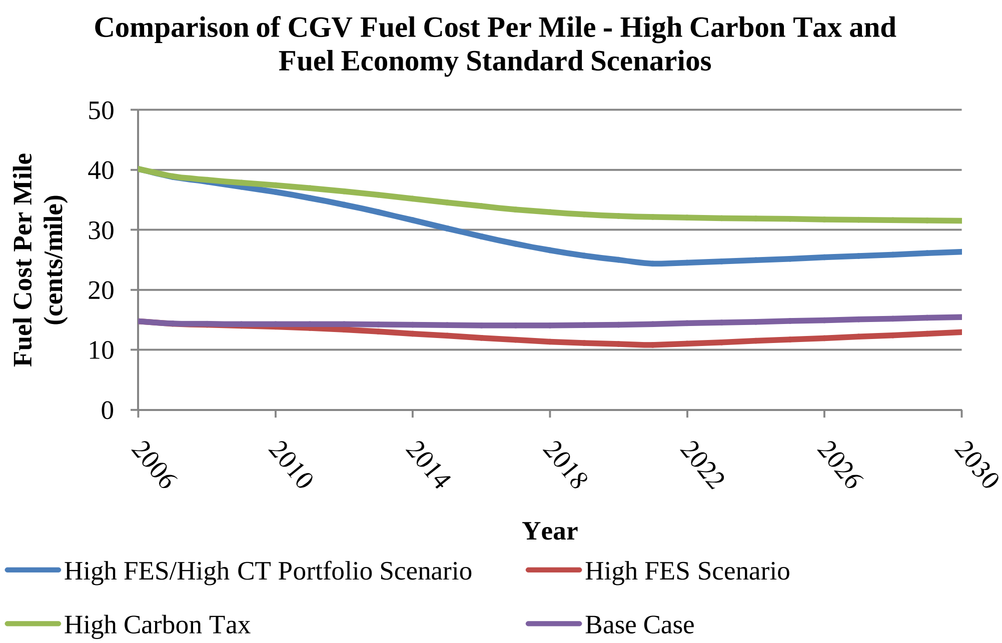

Figure 49 High Carbon Tax/ High Fuel Economy Standard Scenario Results: CGV Fuel Cost Per Mile.

In combination, both of these processes counteract each other within feedback loop *B7*. The positive effect on the cost of travel due to the carbon tax is dampened by the negative effect of the FES. Figure 49 clearly illustrates this feedback effect using the high values case as an example. The fuel cost per mile for gasoline vehicles in the portfolio scenario (blue line) is significantly less (by $.02 to $ .08 per mile) than just the carbon tax case.

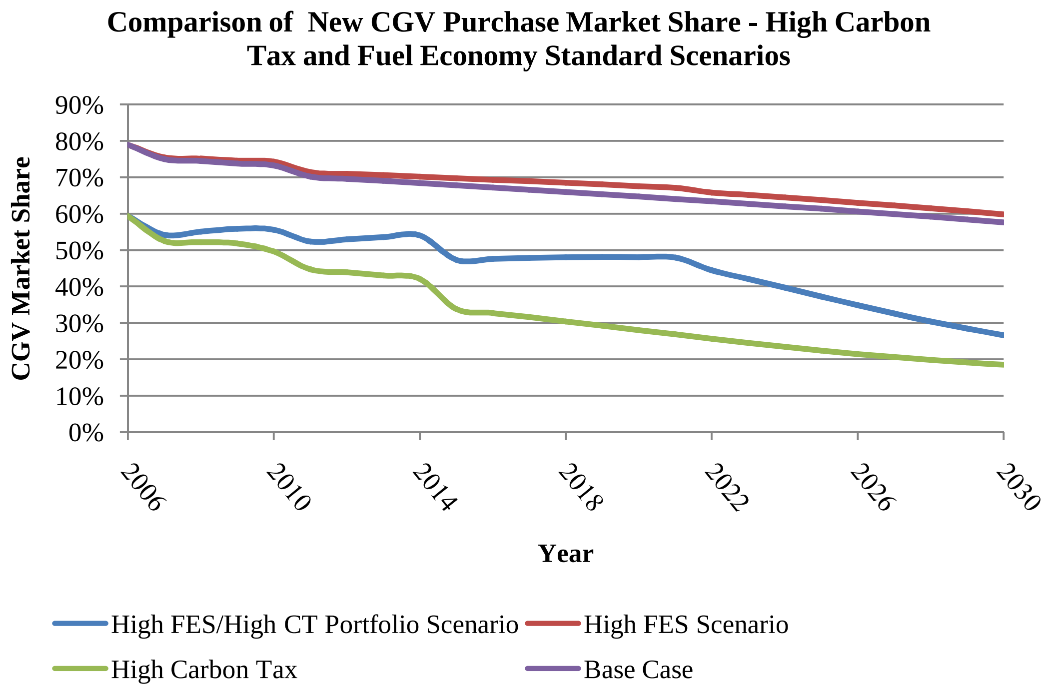

Figure 50 High Carbon Tax/ High Fuel Economy Standard Scenario Results: CGV New Purchase Market Share.

Figure 50 shows the results of this difference. The portfolio scenario results in consumers purchasing more conventional gasoline vehicles than if just a carbon tax were implemented. In comparison, the individual fuel economy standard incentivizes consumers to continue purchasing gasoline vehicles, leading to a slower, more gradual decrease in their market share. The emission consequence of this result is a greater number of fossil fuel burning vehicles entering the LDV population, thus greater operation emissions.

Policy makers should heed policy portfolios explicitly mixing a carbon tax and fuel economy standard as core policies if they want to optimize GHG reductions. Ultimately, all scenarios lead to a long term reduction in the number of gasoline vehicles purchased (of significant magnitudes depending on the scenario), but because of the short and midterm need to drastically cut transportation emissions, implementing this portfolio would not be ideal.

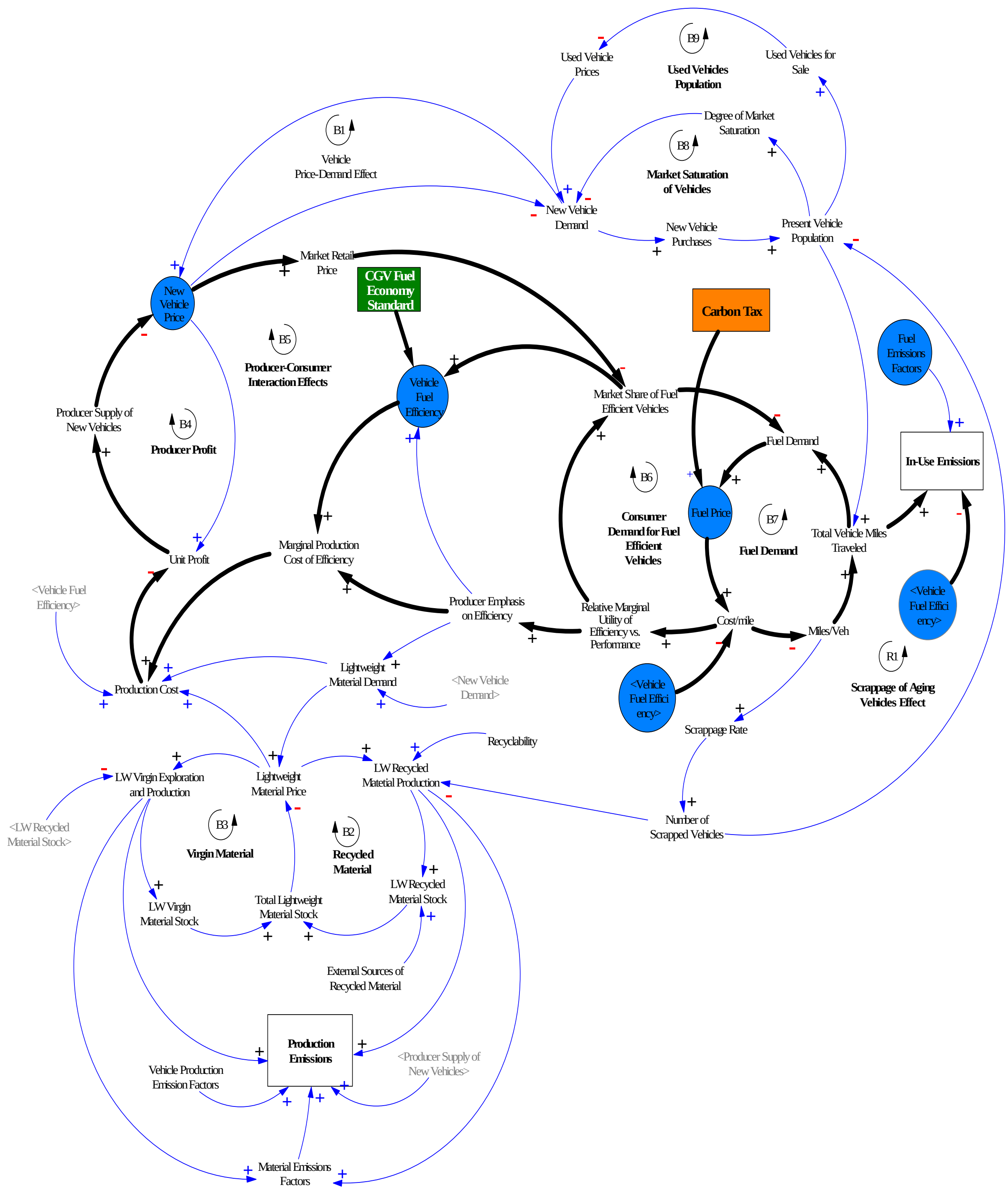

Figure 51 CLIMATS CLD with CGV fuel economy standard/carbon tax portfolio scenario.

For all PHEV subsidy/fuel economy standard scenarios (Scenarios 5, 7, 9, 14, 16, 18, 23, 25, and 27), Figure 55 illustrates that the interplay between balancing loops *B5*, *B6* and *B7* increase PHEV sales (thus reduce emissions), but also increase travel enough to produce more GHGs. These scenarios are interesting because the policy resistance is more moderate than the carbon tax/fuel economy standard cases due to the greater disparity in vehicle price between conventional gasoline vehicles and PHEVs.

The FES, through the marginal cost curves coded in CLIMATS, causes gasoline vehicle prices to increase. The CLD infers qualitatively, that the fuel economy standard (orange box) reduces emission, but inhibits the long term switch to alternative fuel vehicles.

The opposite occurs under the high PHEV subsidy scenario (green box). The drop in price combined with the better fuel economy leads consumers to purchase more PHEVs, reaching over 50% market share by 2020. Further, because consumers are conducting more electricity driven travel, the *Fuel Emissions Factor* (i.e. burning a gallon of gasoline is greater than consuming a kWh of grid electricity) decreases, leading to less tailpipe emissions.

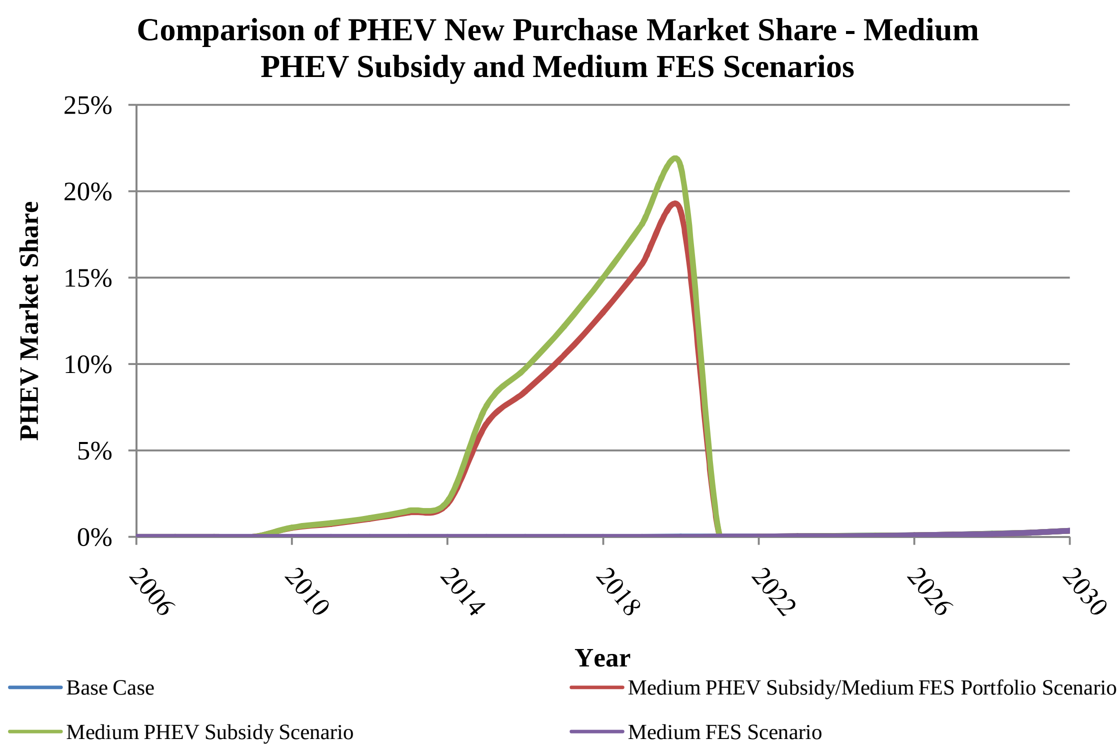

Figure 52 Medium PHEV Subsidy/ Medium Fuel Economy Standard Scenario Results: PHEV New Purchase Market Share.

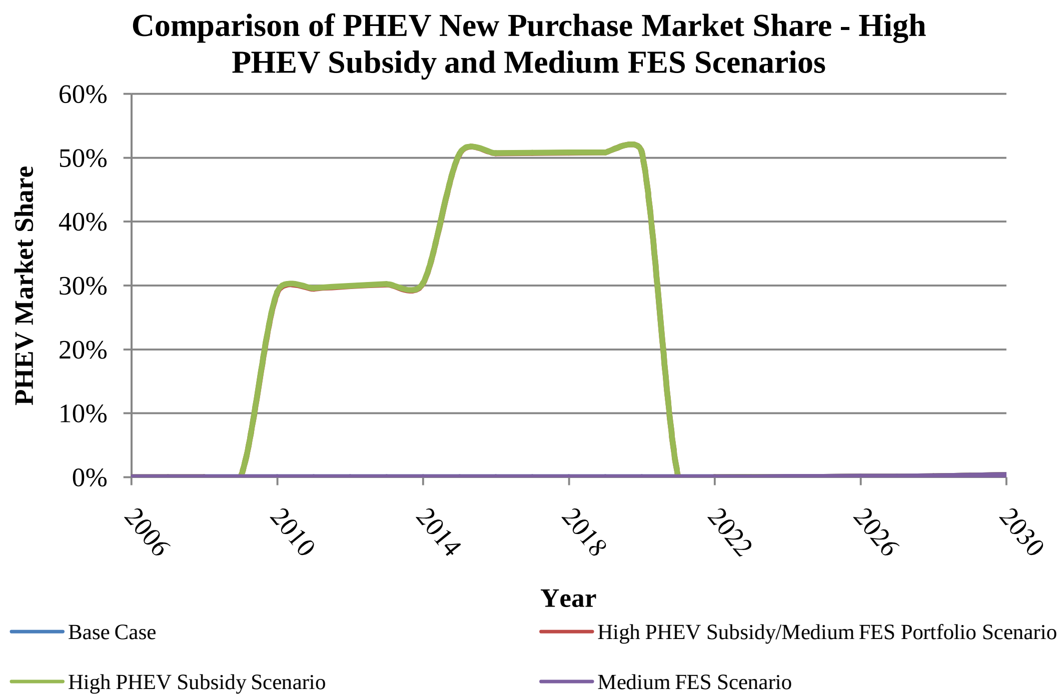

Figure 53 High PHEV Subsidy/ Medium Fuel Economy Standard Scenario Results: PHEV New Purchase Market Share.

The rebound effect also plays a role in these scenarios through loop *B7*. The increase in *Market Share of Fuel Efficient Vehicles* (PHEVs) and increase *Fuel Efficiency* lead to a decrease in *Cost/mile* and therefore an increase in *Miles/vehicle*.

For the portfolio scenario, loops *B5* and *B6* causes enough of an effect to lead to resistance. In combination, the impact of the policy is dependent on the magnitude of the subsidy. A quick glance at Figure 52 indicates that the FES tempers the impact of the subsidy by increasing fuel efficiency even with the increase in gasoline vehicle price. Crunching the numbers reveals that the FES slightly inhibits the sales of PHEVs (*Market Share of Fuel Efficient Vehicles*) by 1% to 4% annually, leading to more gasoline vehicles in the population and therefore more tailpipe emissions. Figure 53 shows that it takes a high PHEV subsidy to negate the sales impediment of the FES.

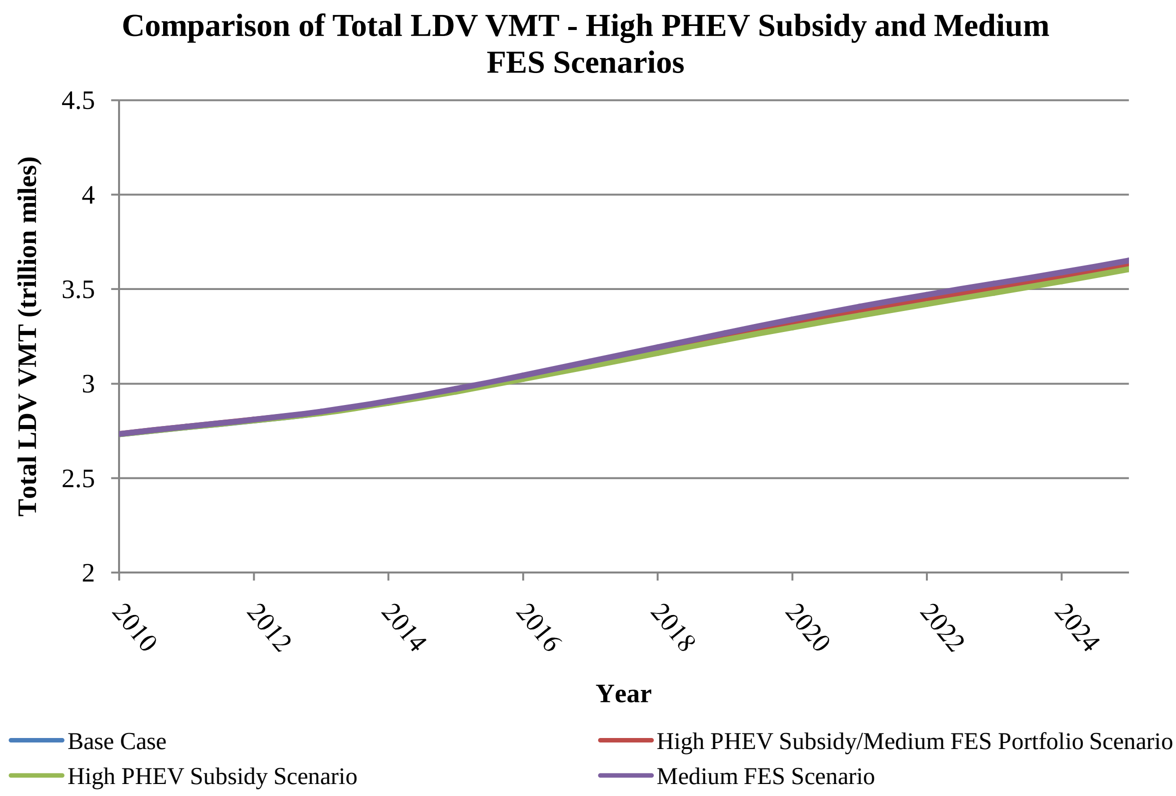

Figure 54 High PHEV Subsidy/ Medium Fuel Economy Standard Scenario Results: Total LDV VMT.

Regarding the policy impact on travel, Figure 54 shows that due to the high share of PHEVs and the slightly higher share of gasoline vehicles being purchased, *Total Vehicle Miles Traveled* increases, falling as the median between the two individual scenarios.

Ultimately, the impedance of emission reductions for a PHEV subsidy/fuel economy standard portfolio is moderate (5% to 15% compared to sum of individual cases), but shows the importance of accounting for system feedbacks. It is noted, that the GHG reductions of the portfolio are still considerable at 50 to 370 million metric tons of CO_2 in 2020 compared to the base case depending on policy magnitudes. Policy makers should recognize that a fuel economy standard may inhibit the effects of a PHEV subsidy if a large scale turnover of the LDV population is the intended consequence. The portfolio does not necessarily reflect a strong case for reducing emissions drastically in the short and midterm.

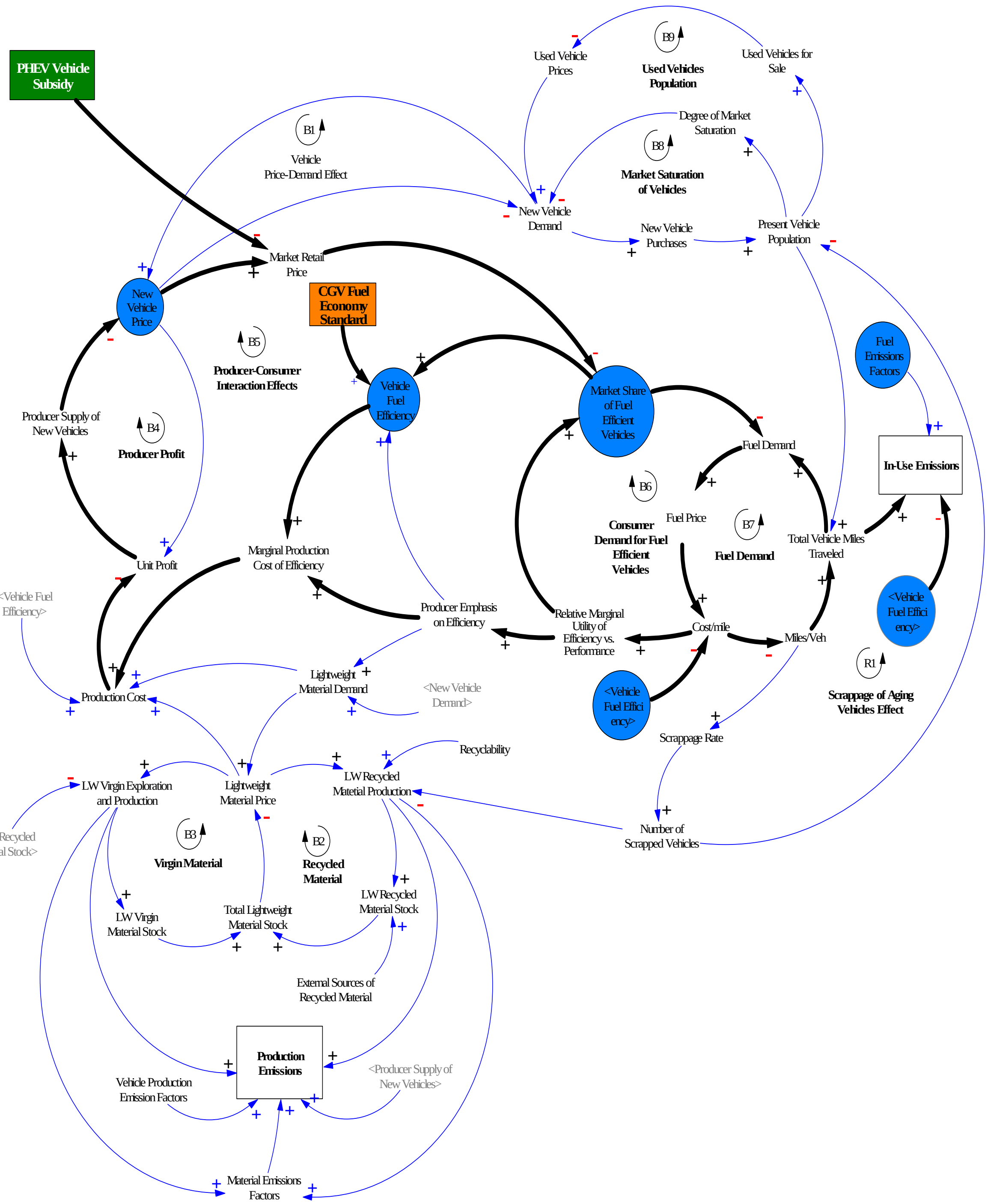

Figure 55 CLIMATS CLD with PHEV subsidy/CGV fuel economy standard portfolio scenario.

5.2.1.2 Policy Synergy

LDV system feedback loops interacted to cause three scenarios of carbon tax/PHEV subsidy portfolios to result in policy synergy. Depending on the magnitude of each policy, the synergistic effects led to a 19% to 96% increase in CO_2 reductions compared to the sum of the individual policy reduction results. Of interest is why the other six scenarios of a carbon tax/PHEV subsidy portfolio resulted in policy resistance. Using the CLD and CLIMATS simulation results, the feedback loops responsible are isolated. Blue circles in the CLD represent variables perturbed or directly important to GHG emissions.

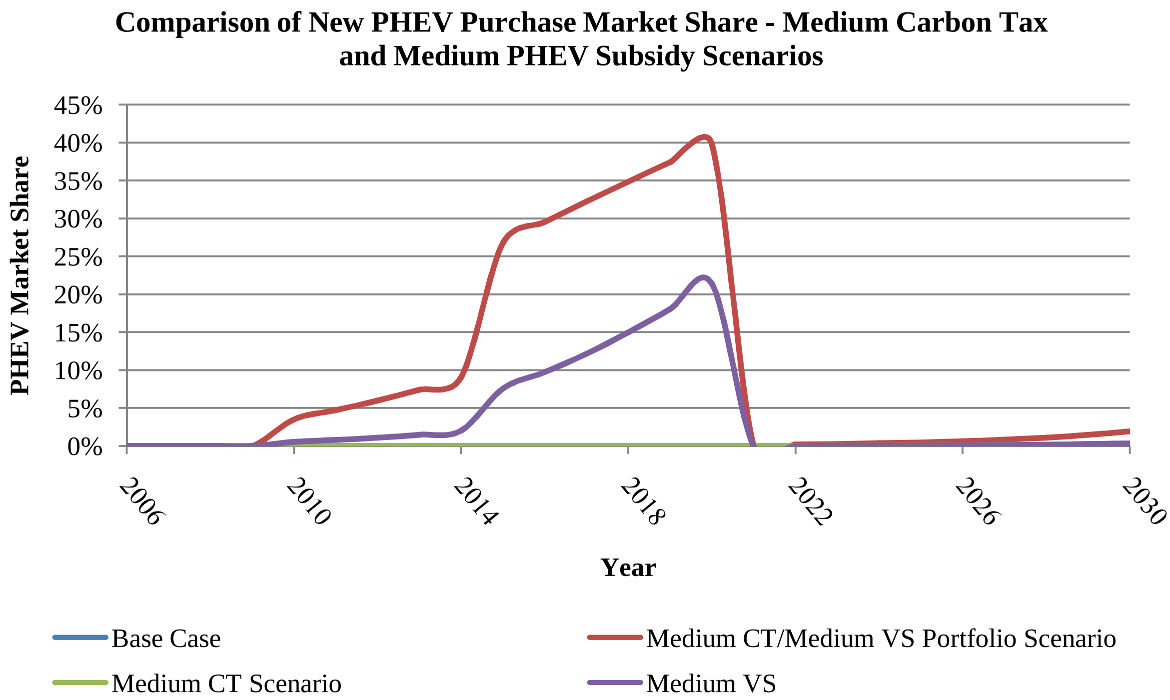

Figure 56 Medium PHEV Subsidy/ Medium Carbon Tax Scenario Results: New PHEV purchase market share.

The three cases of policy synergy – scenarios 20, 28, and 29 – include either a high carbon tax or a medium PHEV subsidy in combination. The same scenario played out in the CLD (Figure 59) indicates that a PHEV subsidy (green box) would increase the *Market Share of Fuel Efficient Vehicles* (PHEV) through a decrease in *Retail Market Price*. The increase in *Vehicle Fuel Efficiency* would decrease the cost of driving (rebound effect), and possibly inhibit the amount of GHGs reduced per vehicle. A carbon tax (orange box) would have the opposite effect by increasing the cost of driving a gasoline vehicle leading to the reverse rebound effect. Also, the increased cost of driving would provide an incentive to purchase an alternative fuel vehicle.

Depending on the magnitude of each policy, the theoretical CLD scenario may differ. For instance, the medium carbon tax case shown in Figure 56 does not provide a significant enough incentive for consumers to purchase PHEVs. On the other hand, the medium PHEV subsidy case provides enough of an incentive, resulting in a 23% market share of new PHEV purchases by 2020.

In combination, both the decrease in *Retail Market Price* of PHEVs due to the subsidy and the increase in *Cost/mile* caused by the carbon tax result in nearly doubling the market share of PHEVs by 2020. In comparison, the high carbon tax/high PHEV subsidy case results in over a 50% market share of PHEV purchases by 2020 (Figure 57) and tailpipe emissions from gasoline vehicles plummets to 300 million metric tons CO_2 (from 1200).

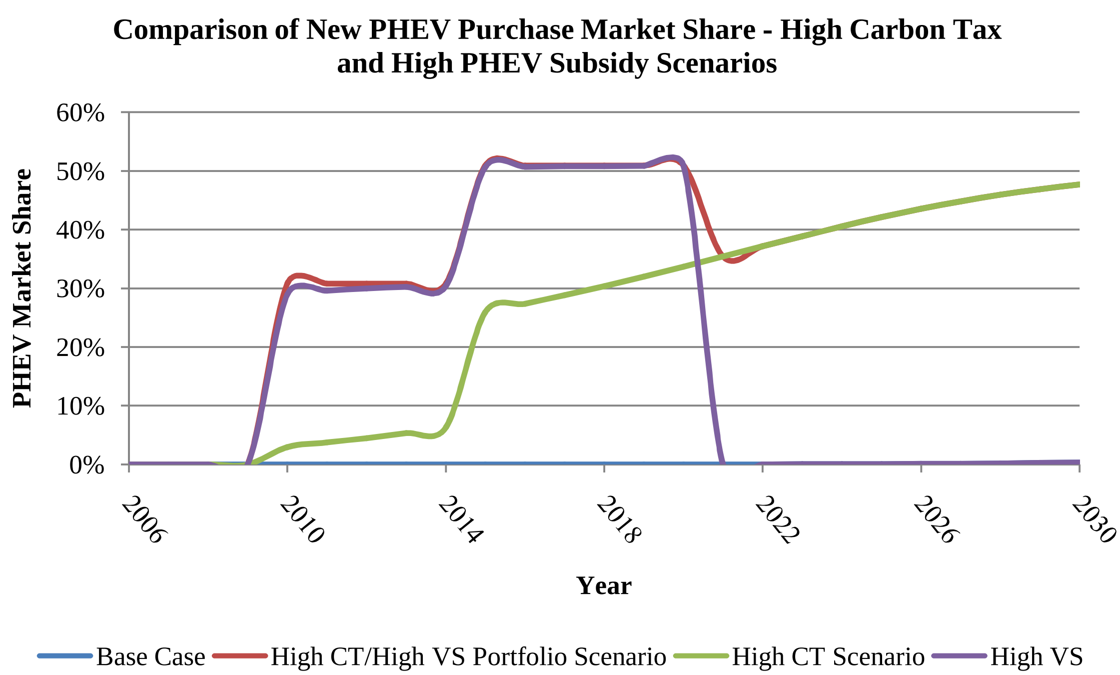

Figure 57 High PHEV Subsidy/ High Carbon Tax Scenario Results: New PHEV purchase market share.

Therefore, a synergy exists when a carbon tax can add an additional incentive for consumers to switch to PHEVs. The "devil is in the details" though. If the carbon tax is too low, the policy acts in much the same way as just a PHEV subsidy, so the portfolio exists in name only (Scenarios 10, 11, 12, and 19). If the subsidy is too high, consumers will trend more to PHEVs (Scenarios 21 and 30), but at a rate identical to the individual policy case.

While the domination of the high subsidy inhibits the combination from acting synergistically, it results in the issue of shifting emissions from the tailpipe to the electric grid.

Figure 58 shows a roughly 2% to 100% increase in upstream fuel emissions from the use of grid electricity in the high combination portfolio option than compared to just the high subsidy or carbon tax cases. Further, because there are now a significant number of PHEVs on the road, those upstream emissions continue to increase over time, resulting in a long term source of GHGs.

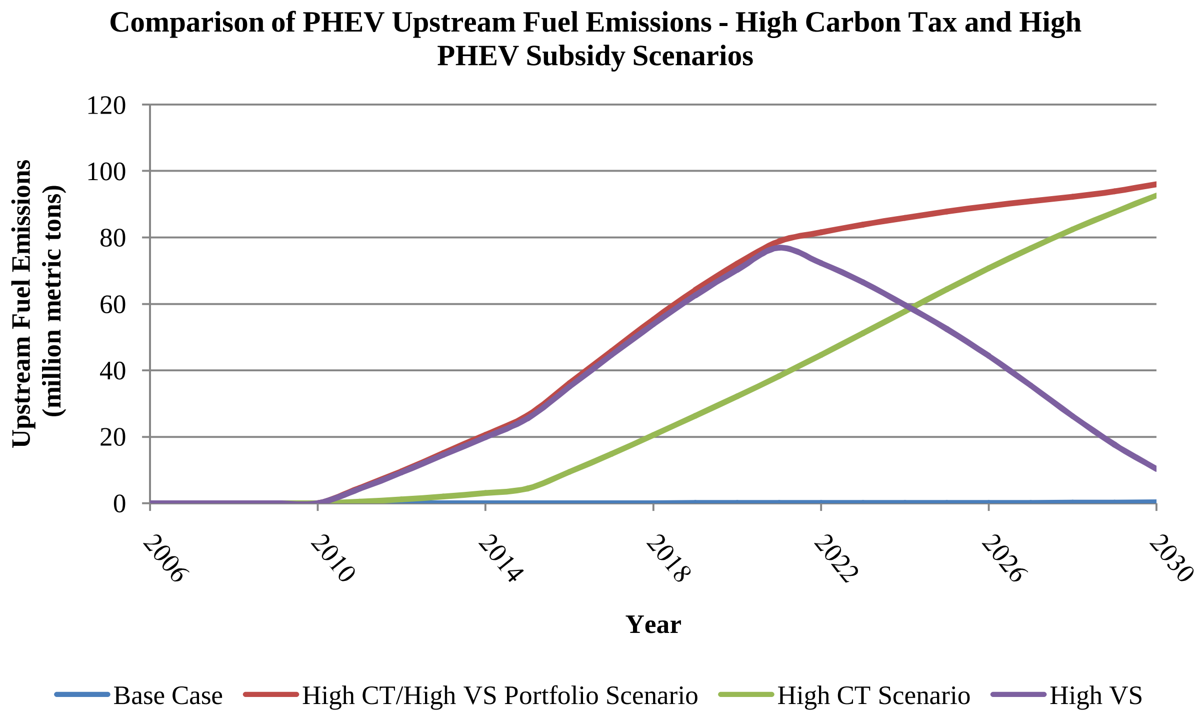

Figure 58 High PHEV Subsidy/ High Carbon Tax Scenario Results: PHEV Upstream Fuel Emissions.

The policy synergy cases indicate that optimizing GHG reductions is not just as simple as finding the correct mix of policy instruments, but also about finding the correct mix of magnitudes. While such a statement may seem obvious, it isn't until the feedbacks are mapped out and quantitative data is produced that policy makers can realize what levels to set each policy. What may look like a theoretical synergy in a decision maker's mental model or even the CLD can easily result in resistance if how aggressive or passive a policy must be is not chosen carefully.

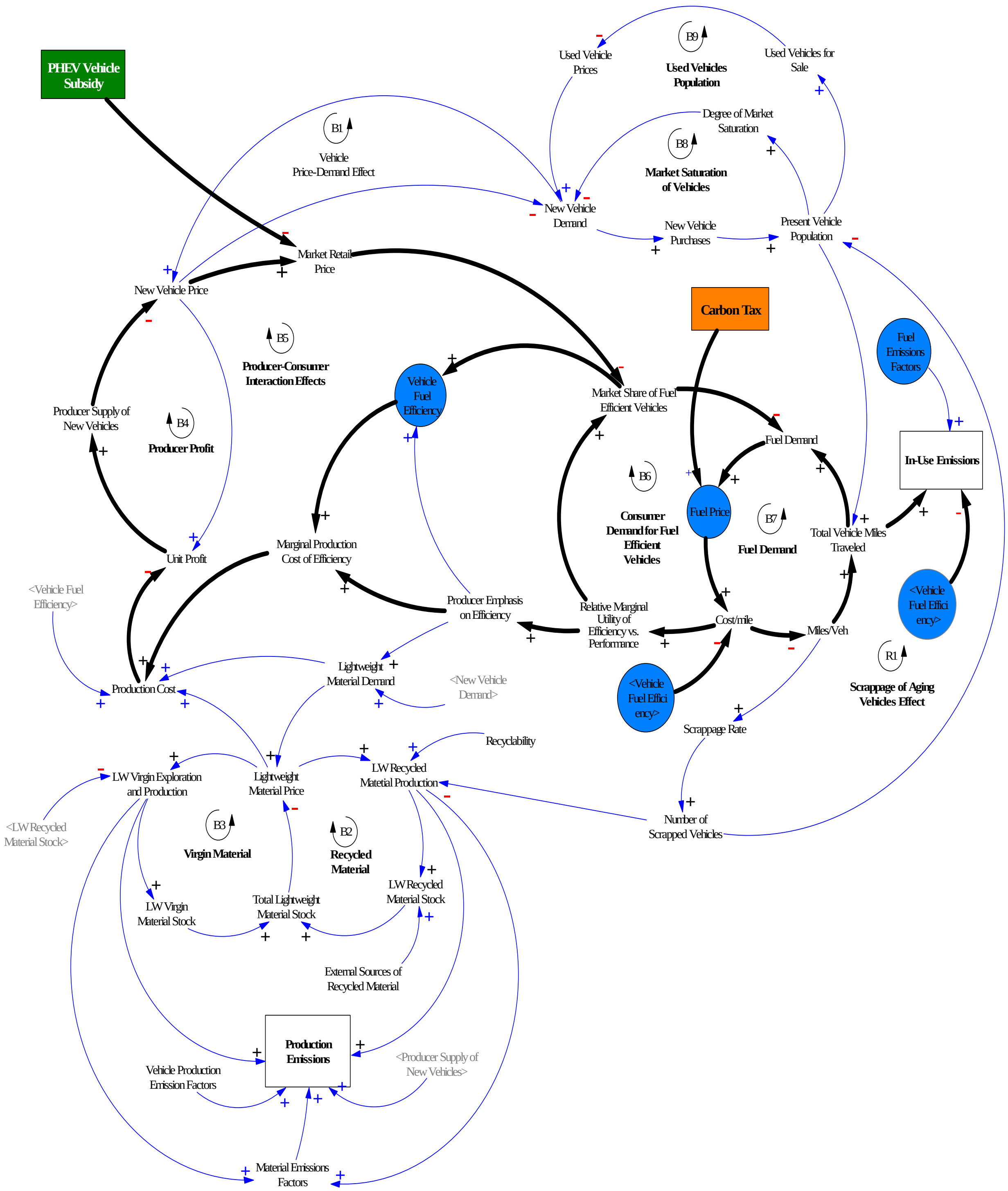

Figure 59 CLIMATS CLD with PHEV subsidy/carbon tax portfolio scenario.

5.2.2 Policy Portfolio Analysis of Additional Unintended Consequences

Individually analyzing each policy portfolio produced findings of potential synergies and resistance as well as what transportation system feedbacks caused those effects. While each of these snapshots is useful and necessary, it is difficult for policy makers to assess a suite of portfolio options and the effects of the feedback interactions just discussed.

The final step in this study's analysis attends to this issue. The following plots illustrate the percent difference of the full range of portfolio scenario emission reductions from a no policy case. To be clear, the data does not show reductions in reference to the sum of the results of the individual policies, so it does not directly analyze for synergy or resistance. Instead, the plots are meant to graphically assess the non linearity of emission reductions, providing additional insight into potential unintended consequences.

For each plot, the axes represent one of the two policies that make up the portfolio and colors are used for emphasis and ease of discussion.

5.2.2.1 Carbon Tax/PHEV Subsidy Portfolios

Figure 60 plots 2020 total LDV emission results for all portfolio combinations of a carbon tax from $0 to $500 per ton CO_2 and a PHEV subsidy from $0 to $6000 per vehicle. A series of unintended consequences are clear. First, it takes a significant carbon tax (up to $225 per ton CO_2) or PHEV subsidy (roughly $2700) to individually reduce emissions by 2%. In combination, only half of those values are needed to reach the same 2% level.

Once policy values exceed those needed to reach 2% individually or in combination, larger emission reductions are made with small marginal increases in magnitude. This *plateau* is an unintended consequence policy makers must take into account. It isn't enough to just implement a policy; it must be significant enough to overcome inhibitions caused by system feedbacks and begin having *any* effect.

A second unintended consequence is the plateau in emission reductions as policy values increase. For example, a portfolio containing a $300 per ton CO_2 carbon tax has the same emissions reductions with both a $5000 and $6000 PHEV subsidy. Policy makers should account for this effect otherwise funds that could be used for other purposes are being allocated with no marginal emissions benefit.

Third, portfolios resulting in greater emission reductions than each individual policy as well as *potential* synergies are more clearly apparent. All scenario values that fall along the diagonal lines (from top left to bottom right) through the middle of the plot are cases of greater emission reductions when implemented in combination. This *window of opportunity* between the tipping point and the plateau is where policy synergies can be found and where policy makers should narrow their choice if multiple policies are sought.

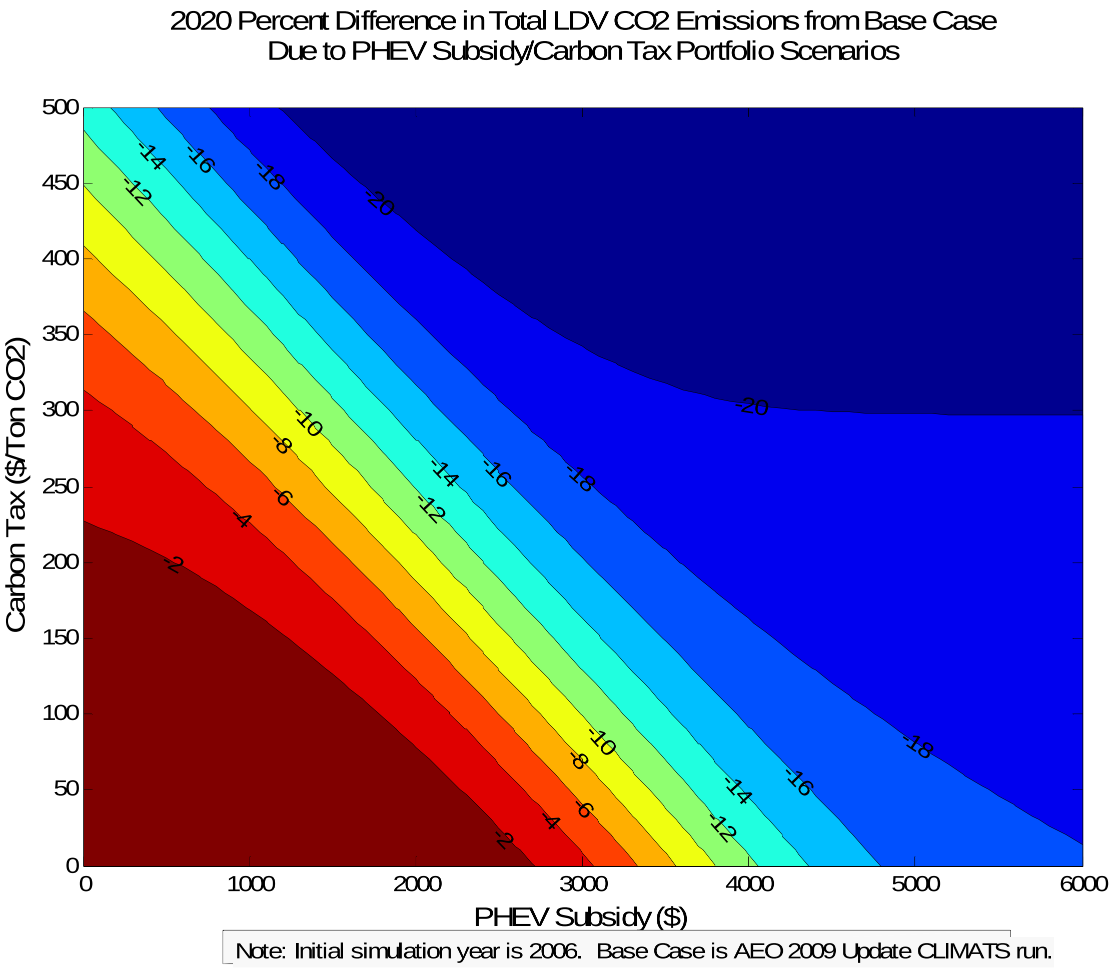

Figure 60 Percent difference of 2020 total LDV emissions from base case: PHEV subsidy and carbon tax portfolios.

An individual assessment of the combinations in the window, such as the method used in the first half of this analysis, is necessary to discern cases of synergy or resistance. For instance, using Figure 60 shows that a \$3000 PHEV subsidy and a \$300 per ton CO_2 carbon tax result in 4% reductions if implemented individually (a sum of 8%). If implemented in combination, the emission reduction is 18%, so it is a case of policy synergy. Conversely, if the PHEV subsidy is increased to $5000 (a 17% reduction) and the carbon tax stays the same (so a sum of 21%), the portfolio combination results in a 19% reduction, therefore policy resistance.

Through this individual scenario assessment, using the plots, another interesting characteristic becomes apparent. The width of the lines (i.e. isopleths) gives important information about the *marginal benefit* of each policy scenario. The marginal benefit can be defined in this instance as the percentage reduction resulting from a unit increase in policy (either individually or in combination). For example, if an individually implemented PHEV subsidy is increased from $3000 to $4000, an additional 8% LDV GHG reduction results. If the same subsidy is increased to $5000 from $4000, only a 4.5% LDV GHG reduction occurs. The benefit of additional subsidy decreases.

This same thinking can be extended to portfolios. Any combined scenarios that fall within the window of opportunity result in synergy and therefore an increasing marginal benefit. In comparison, a $100 carbon tax and $1000 subsidy results in a 2% GHG reduction, but a $200 carbon tax and a $2000 subsidy results in a 6% reduction. Increasing those policy values to $300 and $3000 respectively then results in a 18% reduction, an 3 times increase in marginal benefit.

Therefore, not only do the plots indicate interesting unintended consequences, they also provide policy makers what policy values will give them a "greater bang for the buck". Policies that represent a decrease in marginal benefit may be more costly to result in less than optimal reduction results.

5.2.2.2 CGV Fuel Economy Standard/Carbon Tax Portfolios

Figure 61 plots 2020 total LDV emission results for all portfolio combinations of a carbon tax from $0 to $500 per ton CO_2 and a fuel economy standard on gasoline vehicles from 0% to 3% annually. One significant characteristic of this portfolio is immediately apparent – implementing both policies together is not ideal because of significant policy resistance.

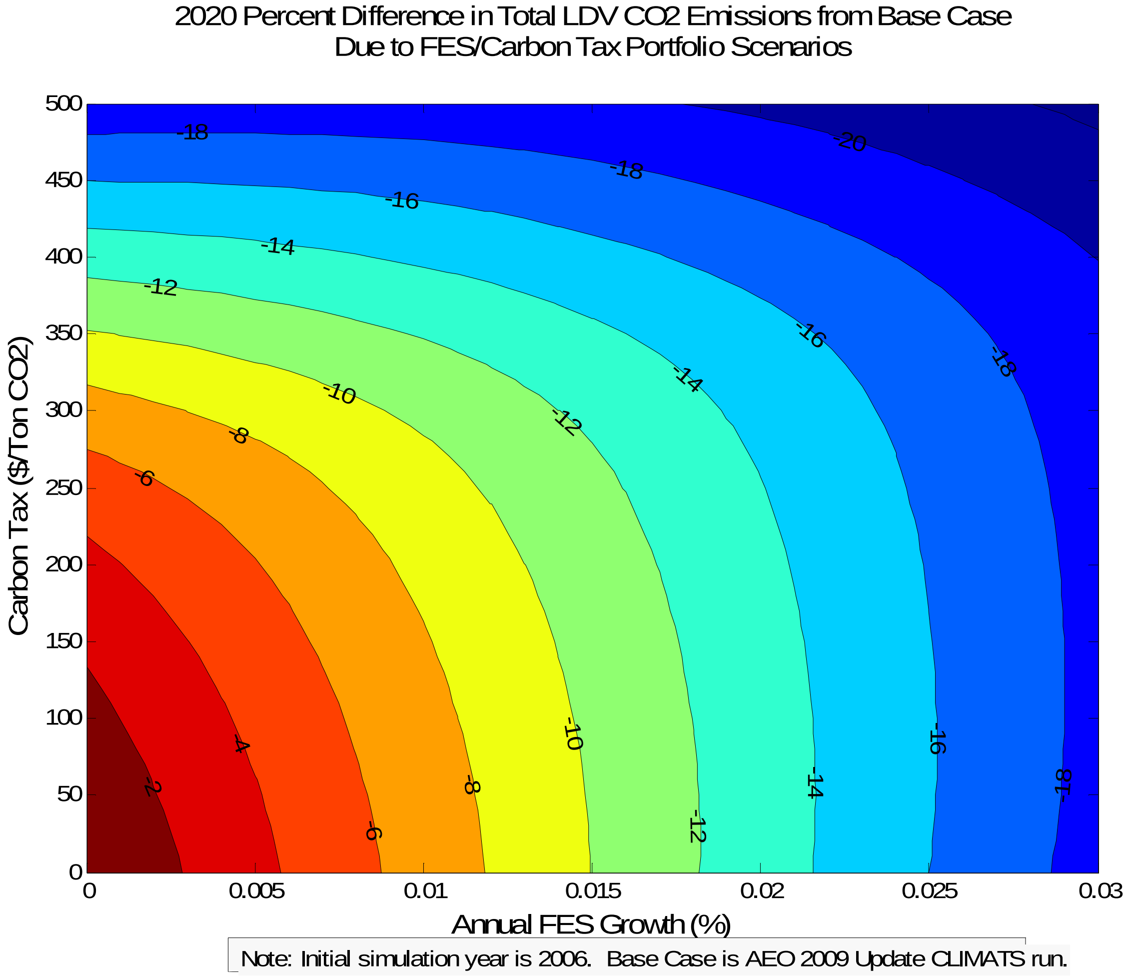

Figure 61 Percent difference of 2020 total LDV emissions from base case: CGV fuel economy standard and carbon tax portfolios.

The *convex effect* of the plot signifies that when implemented in combination, the emission reduction potential is the same or only slightly better than if each were implemented individually. On the contrary, if the reduction isopleths were *concave*, emission reduction potential is considerably greater than if each were implemented individually and potential synergies exist.

The convex effect becomes more pronounced as policy values increase, meaning the feedback effects causing the resistance become more acute with magnitude. Policy makers must understand the small, marginal emission reductions realized when combining both policies. In a case such as this, it is just as relevant to implement just one policy. For instance, it takes a $300 or greater carbon tax to realize any greater GHG reductions, though small, if a 2.5% fuel economy standard is implemented in combination.

Furthermore, the marginal benefits of reductions are different for each policy. The fuel economy standard results in roughly the same marginal decrease in reductions no matter the marginal increase in policy values. This can be simply identified by the width of the isopleths on the x-axis. Compare this to the carbon tax, which as an increasing marginal benefit of reductions. As policy values increase, decision makers can expect greater marginal reductions. In combination, both effects counteract depending on the magnitude of each policy. For example, if the policy combination includes a high carbon tax and a low fuel economy standard, an increasing marginal benefit can be expected. The opposite occurs for a more aggressive standard and a low carbon tax.

5.2.2.3 CGV Fuel Economy Standard/PHEV Subsidy Portfolios

Figure 62 plots 2020 total LDV emission results for all portfolio combinations for a fuel economy standard on gasoline vehicles from 0% to 3% annually and PHEV subsidies from \$0 to \$6000 per vehicle. Of interest is the combination of characteristics from the previous two policy portfolios present in the plot.

For all values of a fuel economy standard, the benefit of an additional PHEV subsidy does not increase until the subsidy is set greater than \$2500 per vehicle plateau. Much like the carbon tax/fuel economy standard plot, policy synergies do not exist until the PHEV subsidy increases. Of note though is the plateau in emissions benefit once subsidy values reach the maximum plotted levels. Greater emission reductions for portfolios compared to individual policy implementation is found in a window of opportunity between both characteristics, such as in the concave isopleths found in the top right corner. Possible synergies may also exist here as well, given the individual analysis discussed previously.

Policy makers must understand that deep emission reductions using both policies are only possible at larger magnitudes. Utilizing smaller values to reach greater reductions, such as in the carbon tax/fuel economy standard portfolios, is not possible. Implementing such a portfolio strategy must be explicitly planned to take advantage of the window of opportunity for greater portfolio GHG reductions and if not, individual policy action may be more useful.

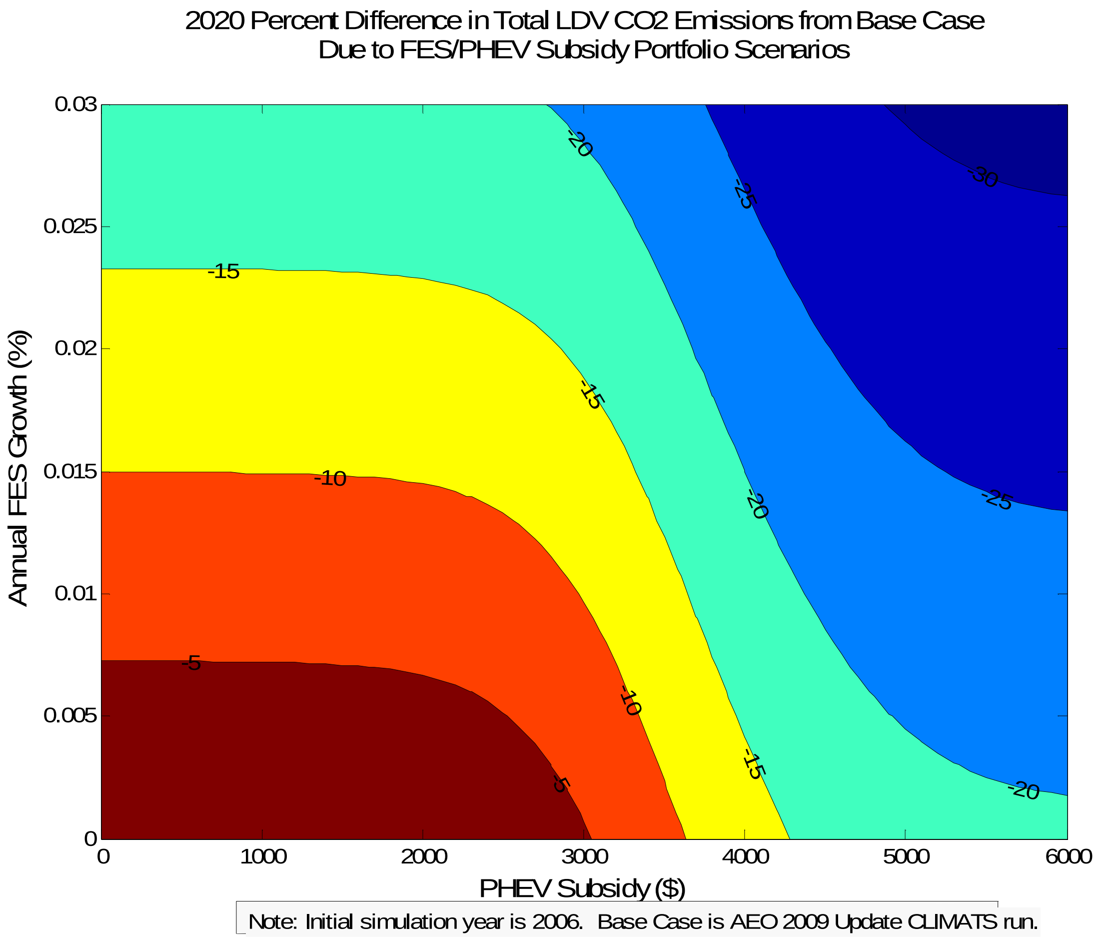

Figure 62 Percent difference of 2020 total LDV emissions from base case: CGV Fuel economy standard and PHEV subsidy portfolios.

6 Conclusions and Recommendations

This study was conducted for two purposes. First, was to demonstrate a more comprehensive approach to conceptualizing transportation climate-energy policy proposals by using a systems dynamics methodology. In doing so, a qualitative CLD was constructed to theoretically discuss important feedback loops vital to GHG reduction policies. The CLIMATS quantitative model was then developed using the CLD as a framework and relevant literature as guidance.

Generally, CLIMATS performed well when validated against the AEO 2009 Update data. While not perfectly mimicking AEO predictions, the model produced usable, reasonably accurate data capable of policy analysis that provided additional and unique insight into transportation feedbacks and emission sources. A sensitivity analysis was conducted to demonstrate the models capabilities and present useful information regarding the expected impact specific system variables could have on emissions reduction potential.

Using CLIMATS, the second purpose of the study was fulfilled. Three often cited LDV emission reduction policies – a carbon tax, gasoline vehicle fuel economy standard, and PHEV subsidy - were simulated both individually and in combination at different magnitudes to assess possible unintended consequences. The analysis resulted in a series of broad insights into the portfolio making process, which is summarized below:

1. *Both the mix of the policies and each instruments magnitude are vital to emission reductions.* The portfolio plots illustrated that system feedbacks cause nonlinearities in GHG reductions. Policy synergy can be met if two policies are implemented in combination, but in many instances, policy resistance is met if values are changed either positively or negatively. It is not enough for policy makers to choose the correct instruments to implement in combination to take advantage of synergy because the correct magnitude is just as important.
2. *Policy resistance occurs more often than not though portfolios do result in greater emission reductions.* Of the 27 portfolio scenarios, 24 resulted in policy resistance and the portfolio plots illustrated that policy combinations do not necessarily lead to synergy. Further, results showed that there is may only a window of opportunity to take advantage

of system feedbacks to result in greater reductions. More often, resistance is met and individual policies could more easily reach intended goals, so the intentions of the policy maker must be made clear. If policy makers are trying to augment existing policies with complementary mechanisms to result in deeper cuts in emissions, values within the window can be used. If policy makers are creating a portfolio to optimize emission reductions, then greater care needs to be taken in choosing policy magnitudes.

3. *Too much policy is not always better and too little policy is often not significant.* The portfolio plots illustrated that marginal benefit plateaus exist. Policy combinations that include a fuel economy standard, for example, need greater policy values to have *any effect*. PHEV subsidies can lead to greater reductions once past a tipping point value, but eventually reach a level where little benefit is realized if the subsidy increases. Special care in setting the optimal, emissions reducing value must be taken.

Given study results, a portfolio approach *can* be used to address the climate-energy conundrum, but within the constraints just discussed. The residence of time of CO_2 in the atmosphere and the sectoral policy approach viewed as necessary to reduce GHGs requires such thinking. Complex feedbacks in systems, such as transportation, can be leveraged to result in higher impact cuts in emissions. To fulfill society's need to reduce GHGs to near zero by mid century (given that it is only 40 years away) synergistic policies is a plausible method of doing so. With that in mind, a series of general policy recommendations can be made based on the analysis, given modeling assumptions made in CLIMATS, and from strictly an emission reduction point of view.

1. *A carbon tax greater than \$300 per ton of CO_2 is necessary to result in meaningful emission reductions, if implemented individually*. The low and medium value carbon tax scenarios resulted in very little GHG reductions and only values between \$300 and \$1000 were significant. Such a value may not be politically feasible as it will be conceived as a considerable tax on gasoline and other fossil fuels, so narrowly focused policies, such as a PHEV subsidy can be used to allow for lower values of the tax, while resulting in the same emission reductions.

2. *A fuel economy standard is not a long term emission reduction solution.* Based on the consumer utility function used in CLIMATS, policy portfolios that include a FES inhibit the long term transition to alternative fuel vehicles. While gradual turnover does occur, the FES dampens the effects of vehicle subsidies and a carbon tax. Policy makers should view a fuel economy standard as a short term solution to address present day environmental issues, such as smog, but not a long term strategy, even in combination.
3. *All policy choices must carefully consider the rate at which the electric grid is decarbonized.* While the electricity generation sector was outside the purview of this study, analyses that included PHEVs showed that more aggressive policies leading to a greater market share of electric battery vehicles ran the risk of shuffling emissions from the tailpipe to power plants. If PHEVs are considered the alternative fuel vehicle of the future by policy makers, complementary actions across *all* sectors of the economy must occur. If electricity decarbonization is not expected to occur quickly, other vehicle options like HEVs, may be more emissions friendly and should be targeted by public policies.

In conclusion, this study provides a unique, usable, and comprehensive methodology for analyzing transportation climate-energy policies. It is unique in that its focus is on the interactions of the many subsystems and dynamics present in the transportation sector, which differs widely from the modeling methods used today. It is usable in that it provides a detailed and focused analysis that can instantly inform the policy making process of not only what policies can reduce emissions, but the magnitude different levels of emission reductions can be met. It is comprehensive in that the basic framework (i.e. CLD) includes numerous subsystems important to transportation, but also how each interacts. By explicitly addressing the web of connections that make up complex systems, the system dynamics approach provides a more accurate representation of policy effects.

7 Validity Concerns

If CLIMATS is viewed as a snapshot in time and under the lens of a seasoned systems modeler, it would be considered a failure and conclusions made would be said to be far from accurate. In fact, the famous systems thinker John Sterman once said that "all decisions are based on models and all models are wrong (Sterman, 2002)." In reality though, CLIMATS should not be viewed as just a singular, frozen model. It should be viewed as a work in progress in the same way systems thinking teaches its students to do.

If all models are wrong – and by definition, all models are simplifications of real world systems, so they *must* be wrong in theory – then CLIMATS is best viewed as an advanced step in the right direction. It provides additional information to policy makers that they may not have received otherwise, of which policy conclusions can be made. It is also just a first step in a series of many variations that ultimately will lead to a more accurate systems model.

Furthermore, according to Sterman, the next step in becoming a systems thinker is the acceptance of weaknesses found in one's work. In accordance with this, the following weaknesses exist in the study that raises validity questions.

The most egregious validity issue is the lack of cohesiveness between the CLD and CLIMATS. A number of dynamics, which were thoughtfully described in the CLD as important, were not included in the quantitative model due to still being under research and development. A reader would be correct in asking why CLIMATS is valid if only a portion of the feedbacks described in the CLD were coded. In short, CLIMATS is still valid as long as the results are placed in context of the assumptions made.

For instance, the fuel economy standard simulations were only for gasoline vehicles and excluded the complex decision making process of producers. The assumption that all new gasoline vehicles would meet the new standard is faulty, but serves the purposes of the analysis by testing the viability of a standard (though optimistic in nature) with other policies. The same can be said of the vehicle subsidies, which in reality have strict quantity limits, so do not last for the length of time simulated in the model. While incorrect, the assumptions made still allowed for an analysis of *how much* a subsidy would need to be to reach certain emission reduction goals.

This omission of endogenous feedbacks and the use of exogenous variables to parameterize those feedbacks also raise another interesting question: are the synergies and resistance discussed in the conclusions robust if additional feedbacks are added to CLIMATS. Adding balancing or reinforcing dynamics to the system may cause study results to change. Given the omitted feedbacks discussed in the CLD, but not included in CLIMATS, it seems as if such additions would trend results to increasing policy resistance.

For example, including a used car market (a balancing loop), theoretically would further lag the transition of new vehicle technology and inhibit the short and midterm impact of a PHEV subsidy. The material subsystem loops (balancing loops) theoretically would reduce the emission impact of alternative fuel vehicles and vehicle lightweighting, providing more policy resistance. On the contrary, if consumer and producer learning dynamics (reinforcing loops) are included, policy synergy could be enforced.

Another concern is the validity of the model over time, especially in regards to policy analysis. The time span of model simulations was short – 26 years – but because broad assumptions about policy implementation were made, the accuracy of emission reductions over time decreases. While the model validated reasonably well with AEO 2009 Update predictions, policy analysis was still kept constrained to 2020 emissions to limit simulation issues.

A third, and equally important, concern is the use of exogenous growth variables in the absence of model dynamics. Systems modeling specifically states that nearly every variable is endogenous and system boundaries must be questioned until this occurs. Unfortunately, due to technological and time limitations, growth factors had to be used. Care was taken to choose factors that are widely cited, defended, and analyzed to limit biases. The sensitivity analysis presented the importance of each of these growth factors and both those governing VMT and new vehicle sales had the highest impact. Fortunately, both factors are augmented in the model by endogenously calculated dynamics (e.g. rebound effect and scrappage-VMT effect), so greater realism and accuracy is assumed here.

Fourth, the policy conclusions only tell half the policy making stories. GHG reduction policies, as with all of public policy, are also discussed within the context of cost. CLIMATS does not calculate the cost to taxpayers and producers of each policy scenario. Decision makers will require such data to assess the political feasibility of the portfolio. The same request can be made to require the number of jobs portfolios will create or eliminate. While not common outputs of climate change related policies, it is a metric used by legislators to rank their options.

In general, any one of these validity issues can be used to doubt any portion of the analysis presented. While a valid criticism, CLIMATS and its underlying assumptions still fulfill its purpose to assess the impacts of policies on GHG emissions. All data should be viewed within the context of this purpose and the details of the model. Future versions of CLIMATS will undoubtedly address many of these validity concerns. Conclusions made in this study are not to be cast aside, but instead used to add to the growing transportation-climate-energy literature and progress the broader policy making discussion.

8 Future Work

If recognizing and accepting the weaknesses of one's work is the first step in becoming a systems thinker, then planning on how to move forward is the next. Considerable work needs to be done to strengthen CLIMATS, through adding additional capabilities and providing more depth to policy analysis. Unfortunately, because of the complex nature of the transportation system, as system boundaries expand, so does the necessary time and effort needed to model and perform analysis. Therefore, these suggestions should be viewed as mid and long term goals.

The current steps need to be taken, in the following order, to realize an all encompassing transportation sector systems model that can simulate any number of climate-energy policies. This list is optimistic (and possibly outlandish), but includes the pieces needed to take CLIMATS to the next level of analysis.

1. A US *macroeconomic submodel* needs to endogenously calculate income, unemployment, and population growth. By including these variables, other important calculations can be made including more accurate scrappage rates, consumer choice of vehicle classes, and other purchasing decisions. A macroeconomic model would also allow for the analysis of an economy wide cap-and-trade policy, which may become a regulatory reality in the coming years, requiring future analysis to account for its effects.
2. A *producer decision making submodel* is needed to interact with the consumer making submodel to calculate vehicle price, endogenously set vehicle attributes, and realistically model CAFE standards. This may be the most difficult to accomplish due to the limitations of the systems dynamics software and the lack of truly understanding how producers make business decisions. Endogenously calculating vehicle attributes and price would be a significant accomplishment to the transportation policy analysis field.
3. A *material choice submodel* is needed to assess the lifecycle emissions resulting from the mining, production, and use of the materials used in vehicles. This is an emissions source that often gets overlooked, so by extension it has not been modeled extensively.

This development would ideally succeed a producer decision making submodel because both are intertwined.

4. *Consumer and producer learning submodels* are vitally important to policy analysis and must be included. The impact of "consumer learning," where, for example, a neighbor owning a PHEV makes it more comfortable for others to purchase their own, is a realistic effect that is being used in other systems models. Also, the effect of economies of scale on reducing average unit costs for vehicles is imperative, especially for alternative fuel vehicles. As vehicle manufacturers gain knowledge of production systems for new types of vehicles, and as the sales volumes for these vehicles increase, one might expect unit costs to decrease once a certain production threshold is reached.
5. A *more realistic consumer choice submodel* may be necessary, but futile. There are numerous consumer utility submodels available and each has been validated to work under specific conditions. The Greene submodel was specifically chosen due to its extensive list of decision attributes and its use in prominent government analysis. Ideally, a new, more accurate consumer submodel will emerge, but it may be necessary to allow for users to switch between different versions and assess the impact of each on analysis.
6. A *consistent and inclusive data set* used across all future CLIMATS analysis is absolutely needed. Among other weaknesses, policy analysis can only be as accurate as the input data, so a master listing of all data is a must. This list should include, at a minimum, historic vehicle sale, populations, and attributes for use in verifying current day simulations and validate future predictions.

The key to the first five, broad additions to CLIMATS is that submodels and the feedbacks each encompasses are kept within the systems dynamics environment as much as the technology will allow. In doing so, interactive dynamics will be sustained and not compromised by the need to transition information from one medium or software to another. While a model that includes all of these aspects would be large and complex, it is keeping all feedback loops intact that is most important. If outside software must be used, special care should be taken to ensure that all dynamics are included; otherwise CLIMATS begins to run into the same problems that Integrated Assessment Models and NEMS incur.

9 Final Thoughts

Former Vice President Al Gore recently stated, “We have to do [climate change legislation] this year…the clock is ticking, because Mother Nature does not do bailouts (Heilprin, 2009).” The urgency (or ticking clock), imbued on the US and the rest of the world to act and reduce GHG emissions increases every day. The urgency becomes more painful once it’s realized that the path to sustainable energy consumption will be difficult. The way of life of most US citizens is firmly wedged within a fossil fuel driven system. To undo this long standing connection in the short term, society must be both forced to change *and* offered a suite of alternative options to ease the transition.

To forcefully change society, all citizens – consumers and producers – must begin to pay for the environmental impacts their choices result in. This is the underpinning of both a carbon tax and a cap and trade policy. By setting a price on planet warming GHGs, the very actions that have led the world to the perilous position it is in will become more costly. The hope is that when faced with making traditional decisions at a greater price or new, less polluting choices at a cheaper rate, consumers will choose the cheaper option. This transition is not that straightforward.

This study showed that consumers are *resilient* to change. It takes a significantly high price on carbon to raise the price of fuel to a level that results in an alteration of consumer decision making. It can be argued that the price of carbon necessary to result in this change is not “politically feasible” due to the outcry from voters as energy prices increase. Can it not also be argued that when the price of carbon becomes politically infeasible it is more likely than not that it is this price that will lead to a change in consumer decision making? Why wouldn’t consumers lash out when faced with a choice they don’t want to make? Consumers and producers must be forced to make the unpopular choice in the short term and political infeasibility may be a necessity.

Yet, the critical changes in decision making need to be made soon and many would argue should have been made before now. To make the choice easier, alternative options can be made available in combination. Policy makers can provide enough financial incentives to make PHEVs affordable now instead of in a decade. For instance, policy makers can initiate a large scale public works project to make homes capable of distributional energy, update power lines, and install alternative fueling infrastructure. All can be done in the name of making the choice of sustainable energy consumption easier.

This study showed that additional incentives aimed at alternatives *can* work. A moderately aggressive PHEV subsidy combined with a carbon tax can lead to more emission reductions and a higher market share of alternative fuel vehicles. The study also showed, though, that the devil is in the details. If all emission sources are not accounted for, society could easily be shuffling emissions from one source to another. Consumers driving more PHEVs can just shift emissions from the tailpipe to the power plant. Consuming more E85 can just shift emissions from burning gasoline to growing and producing crops. Potential emission reductions will be lessened and society may not reach the mid century GHG level it expected to meet.

To avert this, society must view climate change with a wide angle lens. While it may be necessary in this study to breakdown emissions into economic sectors for simplification purposes, each source is all the same. No GHG source is outside the bounds of good policy making or modeling. Once an analysis sets artificial boundaries, its recommendations will be hampered by unintended consequences, emission leakage, and other interactions not captured by the study. Additional policies cannot be viewed within the narrow sector it is implemented in, but instead within the greater whole.

In general, systems dynamics is well positioned to address this and aid in the climate-energy policy making process. Decision makers will choose policies either explicitly to take advantage of synergies or because previously implemented policies aren't working as well as expected and need to be augmented. The types of analysis performed in these pages fit both needs. Proposed policy portfolios can be simulated and tested for interactive effects and by plotting all cases of a portfolio, policy makers can be informed of future results, given system feedbacks. Ultimately, the *hope* is systems dynamics leads to better decisions, though the onus still falls on the *person making the decision*.

Unfortunately, time is running out and the number of choices is decreasing. Analysis showed that given three specific policies, there were more numerous cases of resistance than synergy. The window of opportunity to maximize reduction potential is constrained. The number of pitfalls policy makers can fall in are more numerous than this study lets on due to the political, cultural, financial, and technological hurdles that any portfolio, no matter how optimal, must go through.

In reality, the very need to maximize the consequences of policy decisions is a sign that society is getting nervous. Now, more than ever, society needs to limit future unintended consequences and take out its wide angle lens. Even then, there is no telling if that will be enough. All anyone can hope for is that the select few who are in a position to change the world remembers that no less than the preservation of the planet is at stake.

10 References

2007. Energy Independent and Security Act of 2007, P.L. 110-140, United States.

2009. The Future of National Surface Transportation Policy, Commerce, Science, and Transportation Committee. Ray Lahood, Washington, D.C.

Ackerberg, D., Benkard, C.L., Berry, S., Pakes, A., 2006. Econometric Tools for Analyzing Market Outcomes, in: Heckman, J.J. (Ed.), Handbook of Econometrics.

Agras, J., Chapman, D., 1999. The Kyoto Protocol, CAFE Standards, and Gasoline Taxes. Contemporary Economic Policy 17, 296-308.

An, F., Saur, A., 2004. Comparison of Passenger Vehicle Fuel Economy and Greenhouse Gas Emission Standards Around the World. Pew Center on Global Climate Change.

Anand, S., Dahiya, R.P., Vrat, P., 2005. Investigations of Methane Emissions from Rice Cultivation in Indian Context. Environment International 31, 469-482.

Anderson, S., de Palma, A., Thisse, J.-F., 1992. Discrete Choice Theory of Product Differentiation. MIT Press.

Arroyo, V., Holsinger, H., Wolosin, M., Linquiti, P., Ahmad, S., Adkins, L., Bushinsky, J., Caldwell, S., Diringer, E., Greenwald, J., Juliani, T., Peace, J., Pena, N., 2008. Policies to Reduce Emissions from the Transportation Sector, Congressional Policy Briefs Series. Pew Center on Global Climate Change.

Austin, D., 1999. Economic Instruments for Pollution Control and Prevention – A Brief Overview. World Resources Institute.

Bahrman, S., Lenker, C., Michalek, J., 2002. A Model-Based Approach to Analyze the Effects of Automotive Air Emissions Policy on Consumers, Producers, and Air Quality, Eco Design and Manufacturing.

Bandivadekar, A., Cheah, L., Evans, C., Groode, T., Heywood, J., Kasseris, E., Kromer, M., Weiss, M., 2008. Reducing the Fuel Use and Greenhouse Gas Emissions of the US Vehicle Fleet. Energy Policy 36, 2754-2760.

Bandivadekar, A., Heywood, J., 2004. Coordinated Policy Measures for Reducing the Fuel Consumption of the U.S. Light-Duty Vehicle Fleet. Massachusetts Institute of Technology, Cambridge, MA.

Berry, S., Levinsohn, J., Pakes, A., 1995. Automobile Prices in Market Equilibrium. Econometrica.

Berry, S., Levinsohn, J., Pakes, A., 2004. Differentiated Products Demand Systems from a Combination of Micro and Macro Data: The New Car Market. Journal of Political Economy.

Bush, B., Duffy, M., Sandor, D., Peterson, S., 2008. Using Systems Dynamics to Model the Transition to Biofuels in the United States, Third International Conference on Systems of Systems Engineering. National Renewable Energy Laboratory, Monterey, California.

Bush, G.W., 2008. President Bush Discusses Climate Change, Washington, D.C.

Byrne, J., Hughes, K., Rickerson, W., Kurdgelashvili, L., 2007. American Policy Conflict in the Greenhouse: Divergent Trends in Federal, Regional, State, and Local Green Energy and Climate Change Policy. Energy Policy 35, 4555-4573.

Claes, N., 2007. Intersections of Analysis and Computing: Developing Taxonomy and Scenario Tools for Computer Aided Policy Analysis, College of Liberal Arts/ Public Policy Program. Rochester Institute of Technology, Rochester, NY.

Costanza, R., Wainger, L., Folke, C., Maler, K.-G., 1993. Modeling Complex Ecological Economic Systems. BioScience 43, 545-555.

Das, S., 2000. The Life-Cycle Impacts of Aluminum Body-in-White Automotive Material. Journal of Material.

Davis, S., Diegal, S., 2007. Transportation Energy Data Book. U.S. Department of Energy, Washington, D.C.

Deaton, M.L., Winebrake, J.J., 2000. Dynamic Modeling of Environmental Systems. Springer-Verlag, New York.

EERE, 2009a. Alternative Fuel and Advanced Vehicles, in: U.S. Department of Energy, E.E.a.R.E. (Ed.), Washington, D.C.

EERE, 2009b. Alternative Fuels & Advanced Vehicles Data Center: State & Federal Incentives & Laws, in: U.S. Department of Energy, E.E.a.R.E. (Ed.), Washington, D.C.

EIA, 2007a. Annual Energy Review: Petroleum. Energy Information Administration.

EIA, 2007b. Transportation Demand Module: Key Assumptions. Department of Energy, Washington, D.C.

EIA, 2007c. Transportation Energy Module of the National Energy Modeling System: Model Documentation 2007, in: Forecasting, O.o.I.A.a. (Ed.). Energy Information Agency, Washington, D.C.

EIA, 2008a. Annual Energy Outlook 2008. energy Information Administration.

EIA, 2008b. Transportation Sector Energy Consumption. EIA, Washington, DC, p. http://www.eia.doe.gov/emeu/mer/pdf/pages/sec2_11.pdf.

EIA, 2008c. World Carbon Dioxide Emissions by Region, in: Outlook, I.E. (Ed.). Energy Information Administration.

EIA, 2009a. Annual Energy Outlook 2009 with Projections to 2030: Energy Demand, 2009 Update ed. Energy Information Administration.

EIA, 2009b. Carbon Dioxide Emissions by Sector and Source, in: Outlook, A.E. (Ed.). Energy Information Administration.

Energy and Environmental Analysis, 2002. Analysis and Forecast of the Performance and Cost of Conventional and Electric-Hybrid Vehicles. California Energy Commission.

EPA, 2008. Light-Duty Automotive Technology and Fuel Economy Trends: 1975 Through 2008. Office of Transportation and Air Quality, US Environmental Protection Agency.

FHWA, 2009a. Historical Monthly VMT Report, in: Administration, F.H. (Ed.), Travel Monitoring. U.S. Department of Transportation, Washington, D.C.

FHWA, 2009b. Traffic Volume Trends, in: 1970, H.V.f. (Ed.). Federal Highway Administration.

Fiddaman, T., 2002. Exploring Policy Options with a Behavioral Climate-Economy Model. System Dynamics Review 18, 243-267.

Fiddaman, T., 2007. Dynamics of Climate Policy. Systems Dynamics Review 23, 21-34.

Ford, A., 1995a. Simulating the Controllability of Feebates. System Dynamics Review 11, 3-29.

Ford, A., 1995b. The impacts of large scale use of electric vehicles in southern California. Energy and Buildings 22, 207-217.

Frank, L., Pivo, G., 1994. Impacts of Mixed Use and Density on Utilization of Three Modes of Travel: Single-Occupant Vehicle, Transit, and Walking. Transportation Research Record 1446, 44-52.

Gallagher, K., Collantes, G., Holdren, J., Lee, H., Frosch, R., 2007. Policy Options for Reducing Oil Consumption and Greenhouse-Gas Emissions from the U.S. Transportation Sector, Energy Technology Innovation Policy. Harvard University.

Gillingham, K., Leaver, J., 2008. Impact of Carbon Policy on the Composition of the Vehicle Fleet in New Zealand, Energy, Transport and Sustainability Symposium.

Gillingham, K., Newell, R., Pizer, W., 2008. Modeling Endogenous Technological Change for Climate Policy Analysis. Energy Economics 30, 2734-2753.

Goldberg, P., 1995. Product Differentiation and Oligopoly in International Markets: The Case of the U.S. Automobile Industry. Econometrica 63, 891-951.

Greene, D., 1997. Why CAFE Worked. Oak Ridge National Laboratory, Oak Ridge, Tennessee.

Greene, D., 2001. TAFV Alternative Fuels and Vehicle Choice Model Documentation. Center for Transportation Analysis, Oak Ridge National Laboratory.

Greene, D., Patterson, P., Singh, M., Li, J., 2005. Feebates, Rebates and Gas-guzzler Taxes: A Study of Incentives for Increased Fuel Economy. Energy Policy 33, 757-775.

Greene, D.L., 1992. Vehicle Use and Fuel Economy: How Big is the Rebound Effect. Energy Journal 13, 117-143.

Greene, D.L., Plotkin, S.E., 2001. Energy futures for the US transport sector. Energy Policy 29, 1255-1270.

Greening, L., Greene, D.L., Difiglio, C., 2000. Energy efficiency and consumption -- the rebound effect -- a survey. Energy Policy 28, 389-401.

Greenspan, A., Cohen, D., 1996. Motor Vehicle Stocks, Scrappage, and Sales. Federal Reserve, Washington, D.C.

Han, J., Hayashi, Y., 2008. A System Dynamics Model of CO2 Mitigation in China's Inter-City Passenger Transport. Transportation Research Part D 13, 298-305.

Hansen, J., Sato, M., Kharecha, P., Beerling, D., Berner, R., Masson-Delmotte, V., Pagani, M., Raymo, M., Royer, D.L., Zachos, J.C., 2008. Target Atmospheric CO2: Where Should Humanity Aim. Journal of Open Atmospheric Science 2, 217-231.

Haug, E.J., Choi, K.K., Komkov, V., 1986. Design Sensitivity Analysis of Structural Systems. Academic Press, Orlando, FL.

Heilprin, J., 2009. Gore, others urge CEOs to back climate change deal, The Associated Press.

Hertwich, E., 2005. Life Cycle Approaches to Sustainable Consumption: A Critical Review. Environmental Science & Technology 39.

Heywood, J., Weiss, M., Schafer, A., Bassene, S., Natarajan, V., 2003. The Performance of Future ICE and Fuel Cell Powered Vehicles and Their Potential Fleet Impact. Massachusetts Institute of Technology.

IPCC, 2001. Climate Change 2001: The Scientific Basis, Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change. Intergovernmental Panel on Climate Change, pp. 1-881.

IPCC, 2007. Climate Change 2007: Synthesis Report. Contribution of Working Groups I, II, and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Intergovernmental Panel on Climate Change, Geneva, Switzerland, pp. 1-104.

Jones, C.T., 1993. Another Look at U.S. Passenger Vehicle Use and the 'Rebound' Effect from Improved Fuel Efficiency. Energy Journal 14, 99-110.

Kelly, D., Kolstad, C., 1998. Integrated Assessment Models for Climate Change Control. U.S. Department of Energy.

Kim, H., 2008. Evaluating Life Cycle Cost, Emissions, and Material Use for an Aluminum Intensive Vehicle: Preliminary Analysis, NSF Engineering Research and Innovation Conference, Washington, D.C.

Klimisch, D., 2007. Is an Aluminum Car in Your Future. The Aluminum Association.

Krauthammer, C., 2009. The Net-Zero Gas Tax, The Weekly Standard.

Lee, K., Ni, S., 2002. On the Dynamic Effects of Oil Price Shocks: A Study Using Industry Level Data. Journal of Monetary Economics 49, 823-852.

Liu, Y., Gupta, H., Springer, E., Wagener, T., 2008. Linking Science with Environmental Decision Making. Environmental Modeling and Software, 846-858.

Matthews, H.D., Caldeira, K., 2008. Stabilizing Climate Requires Near-Zero Emissions. Geophys. Res. Lett. 35.

Mau, P., Eyzaguirre, Jaccard, M., Collins-Dodd, C., Tiedemann, K., 2008. The Neighbor Effect: Simulating Dynamics in Consumer Preferences for New Vehicle Technologies. Ecological Economics 68, 504-516.

May, A., Roberts, M., 1995. The Design of Integrated Transport Strategies. Transport Policy 2, 97-105.

Metcalf, G., Paltsev, S., Reilly, J., Jacoby, H., Holak, J., 2008. Analysis of U.S. Greenhouse Gas Tax Proposals. NBER, Cambridge, MA.

Metz, B., Davidson, O., Bosch, P., Dave, R., Meyer, L., 2007. Climate Change 2007: Mitigation. Intergovernmental Panel on Climate Change, New York, NY.

Metz, B., Davidson, O., Coninck, H.d., Loos, M., Meyer, L., 2005. Carbon Dioxide Capture and Storage. Intergovernmental Panel on Climate Change, New York, NY.

Morris, M., 2008. Short-Term Energy Outlook Supplement: Motor Gasoline Consumption 2008: A Historical Perspective and Short-Term Projections. Energy Information Administration.

Mufson, S., 2009. Vehicle Emission Rules to Tighten, Washington Post, Washington, D.C.

Nadel, S., Baden, S., Gray, E., Hewitt, D., Kleisch, J., Langer, T., Misuriello, H., Shipley, A., 2006. Transforming Markets by Combining Federal Tax Credits with Complementary Initiatives. American Council for an Energy-Efficient Economy, Washington, D.C.

Naill, R.F., Belanger, S., Klinger, A., Petersen, E., 1992. An Analysis of Cost Effectiveness of U.S. Energy Policies to Mitigate Global Warming. System Dynamics Review 8, 111-118.

Nordhaus, R., Danish, K., 2003. Designing a Mandatory Greenhouse Gas Reduction Program for the U.S., Policy. Pew Center on Global Climate Change, Arlington, p. 66.

Nordhaus, W., 1993. Optimal Greenhouse-Gas Reductions and Tax Policy in the "DICE" Model. The American Economic Review 83, 313-317.

Nordhaus, W., 2007a. Critical Assumptions in the Stern Review on Climate Change. Science 317, 201-202.

Nordhaus, W., Yang, Z., 1996. A Regional Dynamic General-Equilibrium Model of Alternative Climate-Change Strategies. The American Economic Review 86, 741-765.

Nordhaus, W.D., 2007b. To Tax of Not to Tax: Alternative Approaches to Slowing Global Warming. Review of Environmental Economics and Policy 1, 26-44.

NRC, 2002. Effectiveness and Impact of Corporate Average Fuel Economy (CAFE) Standards. National Research Council, Washington, D.C.

O'Driscoll, P., 2007. A Drought for the Ages, USA Today.

Obama, B., 2008. Barack Obama and Joe Biden: New Energy for America.

Obama, B., Biden, J., 2008. New Energy for America.

Pachauri, R., Reisinger, A., 2007. Climate Change 2007: Synthesis Report, Intergovernmental Panel on Climate Change Fourth Assessment Report. United Nations, pp. 1-24.

Pearce, D., 1991. The Role of Carbon Taxes in Adjusting to Global Warming. The Economic Journal 101, 938-948.

Piattelli, M.L., Cuneo, M.A., Bianchi, N.P., Giuseppe, S., 2002. The control of goods transportation growth by modal share re-planning: the role of a carbon tax. . System Dynamics Review 18, 47-69.

Plotkin, S., 2000. Technologies and Policies for Controlling Greenhouse Gas Emissions from the U.S. Automobile and Light Truck Fleet. Center for Transportation Research, Argonne National Laboratory, Argonne, Illinois.

Plotkin, S., 2007. Examining New US Fuel Economy Standards. Environment 49, 8-19.

Rose, A., Oladosu, G., 2002. Greenhouse Gas Reduction Policy in the United States: Identifying Winners and Losers in an Expanded Permit Trading System. The Energy Journal 23, 1-18.

Saur, K., 1995. Foudations for Life Cycle Analysis of Automotive Structures: The Potential of Steel, Aluminum, and Composites. Society of Automotive Engineers.

Sawin, E., Jones, A., Fiddaman, T., Siegel, L., Wright, D., Frank, T., Barkman, A., Cummings, T., von Peter, F., McGlade, J., Correll, R., Sterman, J., 2009. Current Emissions Reductions Proposals in the Lead-Up to COP-15 are Likely to be Insufficient to Stabalize Atmospheric CO2 Levels: Using C-Roads - A Simple Computer Simulation of CLimate Change to Support Long-Term Climate Policy Development.

Saysel, A.K., Barlas, Y., Yenig, O., 2002. Environmental Sustainability in an Agricultural Development Project: A Systems Dynamics Approach. Journal of Environmental Management 64, 247-260.

Schar, C., Vidale, P., Luthi, D., Frei, C., Haberli, C., Liniger, M., Appenzeller, C., 2004. The Role of Increasing Temperature Variability in European Summer Heatwaves. Nature 427, 332-336.

Skerlos, S., Winebrake, J., 2007. Implications of Greenhouse Gas Policies on Material Flows: A Life Cycle Approach Integrating Engineering, Public Policy, and Economics, Materials Use, Science, Engineering, and Society Program Annual Report. National Science Foundation.

Small, K., Dender, K.V., 2007. Fuel Efficiency and Motor Vehicle Travel: The Declining Rebound Effect. Energy Journal 28, 25-51.

Sorrell, S., 2003. Interaction in EU Climate Policy, in: Sorrell, S. (Ed.). SPRU, University of Sussex, Sussex, UK.

Sterman, J., 2000. Business Dynamics: Systems Thinking and Modeling for a Complex World. McGraw Hill, New York, NY.

Sterman, J., 2002. All Models are Wrong: Reflections on becoming a Systems Scientist. System Dynamic Review 18, 501-531.

Sterman, J., 2008. Risk Communication on Climate: Mental Models and Mass Balance. Science 322, 532-533.

Stern, N., 2007. The Economics of Climate Change: The Stern Review, Cambridge, UK.

Supple, D., 2004. Managing the Transition toward Self-Sustaining Alternative Fuel Vehicle Markets: Policy Analysis Using a Dynamic Model, Technology and Policy Program, Engineering Systems Division. Massachusetts Institute of Technology, p. 97.

Tan, R., Khoo, H., 2005. An LCA Study of a Primary Aluminum Supply Chain. Journal of Cleaner Production 13, 607-618.

Tol, R., 2006. Integrated Assessment Modelling. Research Unit Sustainability and Global Change, Hamburg University, Hamburg, Germany.

Tol, R., 2007. The Double Trade-off Between Adaptation and Mitigation for Sea Level Rise: An Application of Fund. Mitigation and Adaptation Strategies for Global Change 12, 1573-1596.

Trenberth, K., Shea, D., 2006. Atlantic Hurricanes and Natural Variability in 2005. Geophysical Research Letter 33, 1-8.

Turrentine, T., Kurani, K., 2007. Car Buyers and Fuel Economy? Energy Policy 35, 1213-1223.

Vieira, J., Moura, F., Viegas, J.M., 2007. Transport Policy and Environmental Impacts: The Importance of Multi-Instrumentality in Policy Integration. Transport Policy 14, 421-432.

Wang, J., Lu, H., Peng, H., 2008. System Dynamics Model of Urban Transportation System and Its Application. Journal of Transportation Systems Engineering and Information Technology 8, 83-89.

Wang, M.Q., 1996. Development and Use of the GREET Model to Estimate Fuel-Cycle Energy Use and Emissions of Various Transportation Technologies and Fuels. Center for Transportation Research, Energy Systems Division, Argonne, Illinios.

Wigley, T.M., 2006. A Combined Mitigation/Geoengineering Approach to Climate Stabalization. Science 314, 452-454.

Winebrake, J., Creswick, B., 2003. The Future of Hydrogen Fueling Systems for Transportation: An Application of Perspective-based Scenario Analysis using the Analytic Hierarchy Process. Technological Forecasting and Social Change 70, 359-384.

Appendix 1 Causal Loop Diagram Variable Details

Appendix 1.1 Causal Loop Variable Listing, Description, and Units

Variable *(alphabetical)*	Description	Units	Component of Loop?
Cost/Mile	The cost to the consumer per vehicle mile driven.	dollars / mile	B6, B7, R1
Degree of Market Saturation	The percentage of maximum saturation of vehicle ownership in the United States. As total Market Saturation increases, *New Vehicle Purchases* increase, and vice versa.	percent	B8
External Sources of Recycled Material	Amount of recycled material drawn from sources other than scrapped vehicles -- for instance, aluminum recycled from cans used in vehicle production.	kilograms	No
Fuel Demand	Consumer demand for vehicle fuel, directly related to the *Total Miles Traveled* for the vehicle population.	gallons	B6, B7, R1
Fuel Emissions Factors	Conversion factors, including the carbon fraction of gasoline, that equate fuel consumption to emissions produced; note that these could capture upstream emissions (emissions from the production and delivery of fuel to the vehicle) and downstream emissions (emissions from the use of the fuel in the vehicle).	CO_2 / (gallon of fuel consumed)	No
Fuel Price	The price of a gallon gasoline equivalent (gge) of vehicle fuel.	dollars / gge	B1, B6, B7R1
In-Use Emissions	Total tailpipe emissions (CO_2) emitted by the vehicle population per year.	million metric tons of CO_2	No
Lightweight Material Demand	Amount of lightweight material (e.g., aluminum) needed to produce the new year's vehicle population. Lightweighting is one method producers can use to meet efficiency goals.	kg/yr	No
Lightweight Material Price	The price of lightweight materials (e.g., aluminum) needed to manufacture the *New Vehicle Purchases*.	dollars/ kilogram	B2, B3
LW Recycled Material Production	The amount of recycled lightweight material produced from the *Number of Scrapped Vehicles* in the given year.	kilograms/yr	B2
LW Recycled Material Stock	The total amount of recycled lightweight material available for vehicle production; this is determined by the material recycled from the *Number of Scrapped Vehicles* and other external sources.	kilograms	B2
LW Virgin Exploration and Production	The amount of new virgin lightweight material produced annually.	kilograms/yr	B3
LW Virgin Material Stock	The total amount of virgin lightweight material available for vehicle production.	kilograms	B3
Marginal Production Cost of Efficiency	The cost to the producer for increasing fuel efficiency in a new vehicle by one mile per gallon.	dollars / mile per gallon	B5
Market Retail Price	The retail price of a new vehicle.	dollars/vehicle	B5
Market Share of Fuel Efficient Vehicles	The share of the total vehicle market belonging to fuel efficient vehicles; this is affected by consumers' utility functions.	percent	B6
Material Emissions Factors	Emissions per unit of material (virgin or recycled) produced.	million metric tons of CO_2 / kg of material	No
Miles/Veh.	Miles traveled per vehicle in the *Present Vehicle Population* for a given year.	miles/vehicle-yr	B7, R1
New Vehicle Demand	The number of new vehicles demanded for a given year.	vehicles/yr	B1, B9, B5, B8
New Vehicle Purchases	The number of new vehicles purchased in a year; determined by the degree of market saturation and the price of a new vehicle vs. the price of a used vehicle.	vehicles/yr	B9, B5, B8
New Vehicle Price	The price of a new vehicle, determined by market equilibrium achieved by producers (maximizing profit) and consumers (maximizing utility).	dollars	B4, B5, B1
Number of Scrapped Vehicles	The number of vehicles scrapped per year, determined by the scrappage rate of each model year vehicle population.	vehicles/yr	R1
Present Vehicle Population	Total vehicle population in a given year.	vehicles	R1, B8, B9
Producer Emphasis on Efficiency	The extent to which producers emphasize fuel efficiency as a vehicle attribute.	emphasis value	No
Producer Supply of New Vehicles	Producers' supply of new vehicles in a given year.	vehicles/yr	B4, B1

Variable *(alphabetical)*	Description	Units	Component of Loop?
Production Cost	Total cost of vehicle production based on the cost of materials and technologies needed to meet vehicle efficiency and performance attributes.	dollars/vehicle	No
Production Emissions	Emissions (e.g., CO_2) produced in the manufacturing stage of the *New Vehicle Purchases* population per year.	million metric tons of CO_2/yr	No
Recyclability	The percentage of total available recycled material that is reusable after the recycling process.	%	No
Relative Marginal Utility of Efficiency vs. Performance	The ratio of consumer utility of one mile per gallon of fuel efficiency to one unit of performance, where in this example vehicle acceleration and horsepower are used as proxies for performance.	units of utility / mile per gallon	B6
Scrappage Rate	The percentage of each model year vehicle population that is scrapped each year.	%	R1
Total Lightweight Material Stock	The total amount of lightweight material (both virgin and recycled) available for vehicle production in a given year.	kilograms	B2, B3
Total Vehicle Miles Traveled	The total miles traveled per year by the vehicle population.	miles/year	B7, R1
Unit Profit	Producer profit on each vehicle sold in a given year.	dollars / vehicle	B4
Used Vehicle Prices	The price of used vehicles in a given year.	dollars / vehicle	B9
Vehicle Fuel Efficiency	The fuel efficiency of the vehicle population.	miles / gallon of fuel	No
Vehicle Production Emission Factors	Emissions due to the production of vehicles.	Million metric tons of CO_2 / vehicle	No

Appendix 1.2 Causal Feedback Loop Classification and Components

Loop ID	Balancing (-) or Reinforcing (+)	Full Name	Components	External Elements Influencing Loop
R1	Reinforcing *(+)*	Scrappage of Aging Vehicles Effect	Number of Scrapped Vehicles Present Vehicle Population Total Vehicles Miles Traveled Fuel Demand Fuel Price Cost/mile Miles/Veh. Scrappage Rate	Present Vehicle Population New Vehicle Purchases Market Share of Fuel Efficient Vehicles
B1	Balancing (-)	Vehicle Price-Demand Effect	Producer Supply of New Vehicles New Vehicle Price New Vehicle Demand	Unit Profit Used Vehicle Prices Degree of Market Saturation
B2	Balancing	Recycled Material	Lightweight Material Price LW Recycled Material Production LW Recycled Material Stock Total Lightweight Material Stock	Recyclability Number of Scrapped Vehicles External Sources of Recycled Material LW Virgin Material Stock Lightweight Material Demand
B3	Balancing	Virgin Material	Lightweight Material Price LW Virgin Exploration and Production LW Virgin Material Stock Total Lightweight Material Stock	Lightweight Material Demand LW Recycled Material Stock
B4	Balancing	Producer Profit	New Vehicle Price Unit Profit Producer Supply of New Vehicles	Production Cost New Vehicle Demand
B5	Balancing	Producer-Consumer Interaction Effects	Market Retail Price New Vehicle Price New Vehicle Demand New Vehicle Purchases Present Vehicle Population Total Vehicles Miles Traveled Fuel Demand Fuel Price Cost/mile Miles/Veh. Scrappage Rate Number of Scrapped Vehicles LW Recycled Material Production LW Recycled Material Stock Total Lightweight Material Stock Lightweight Material Price Production Costs Unit Profit Producer Supply of New Vehicles	Vehicle Fuel Efficiency Marginal Production Cost of Efficiency Lightweight Material Demand Recyclability External Sources of Recycled Material LW Virgin Material Stock Degree of Market Saturation Used Vehicles Prices
B6	Balancing	Consumer Demand for Fuel Efficient Vehicles	Market Share of Fuel Efficient Vehicles Fuel Demand Fuel Price Cost/mile Relative Marginal Utility of Efficiency vs. Performance	Total Vehicle Miles Traveled Marginal Utility of Performance New Vehicle Price
B7	Balancing	Fuel Demand	Fuel Demand Fuel Price Cost/mile Miles/Veh. Total Vehicle Miles Traveled	Market Share of Fuel Efficient Vehicles Present Vehicle Population Vehicle Fuel Efficiency
B8	Balancing	Market Saturation of Vehicles	Degree of Market Saturation New Vehicle Demand New Vehicle Purchases Present Vehicle Population	Number of Scrapped Vehicles Used Vehicle Prices
B9	Balancing	Used Vehicles Population	Used Vehicle Prices New Vehicle Demand New Vehicle Purchases Present Vehicle Population Used Vehicles for Sale	Degree of Market Saturation New Vehicle Price Number of Scrapped Vehicles.

Appendix 2 CLIMATS Quantitative Model Details

Appendix 2.1 CLIMATS Model Variables, Descriptions, and Subsystem Components

Variable *(alphabetical)*	Full Name	Description	Subsystem(s)
% Driven on Gasoline	Percent Driven on Gasoline	User inputted values that allocate the percentage of time each vehicle class/vehicle fuel type is driven using gasoline. Values not inputted for FFVs. Variable only used for vehicle types not subject to the Fuel Choice Submodel.	Cohort
% Use of Fuel	Percent Use of Fuel	Allocates the percent use of each fuel (gasoline, diesel, electricity, and E85) for each vehicle class/vehicle fuel type from the input variables *% Driven on Gasoline* and the Fuel Choice Submodel.	Cohort
Acceleration	Acceleration	Inputs the acceleration of each new vehicle class/vehicle fuel type entering the market.	Producer
Aging Vehicles	Aging Vehicles	A flow variable in the vehicle population cohort submodel that simulates the aging of vehicles from year to year.	Cohort
Annual Change in Fuel Availability	Annual Change in Fuel Availability	Flow variable that calculates the annual change in the availability of each fuel type.	Producer
Annual Change in Fuel Economy	Annual Change in New Vehicle Fuel Economy	Flow variable that calculates the annual change in new vehicle class/vehicle fuel type fuel economy.	Cohort, Consumer, Producer
Annual Change in Maintenance Cost	Annual Change in New Vehicle Maintenance Cost	Flow variable that calculates the annual change in the maintenance cost for new vehicles.	Consumer, Producer
Annual Change in Make/Model Availability	Annual Change in Make/Model Availability	Flow variable that calculates the annual change in the number of make/models available for each vehicle fuel type.	Producer
Annual Change in Range	Annual Change in New Vehicle Range	Flow variable that calculates the annual change in the range (per tank of fuel) of new vehicles.	Producer
Annual Change in Sales	Annual Change in New Vehicle Sales	Inputs the annual percentage change in vehicle sales. Can be used in model scenarios to simulate different macroeconomic trends in consumers buying vehicles.	Consumer
Annual Change in Untaxed Fuel Price	Annual Change in Untaxed Fuel Price	Flow variable that calculates the annual change in all fuel prices due to exogenous perturbations.	Consumer
Annual Change in Vehicle Price	Annual Change in New Vehicle Price	Flow variable that calculates the annual change in the price of new vehicles.	Producer
Annual Change in VMT	Annual Change in Individual Vehicle Miles Traveled	A flow variable that represents the annual change in the VMT of each vehicle in use in all model cohorts. Change occurs due to macroeconomic trends captured in *Annual Growth in VMT* and the rebound effect captured in *Change in VMT FC*.	Cohort
Annual Growth in VMT	Annual Growth in Individual Vehicle Miles Traveled	Inputs the annual percentage change in VMT. Can be used in model scenarios to simulate different macroeconomic trends in consumers buying vehicles.	Cohort
Annual LDV Emissions	Annual Light Duty Vehicle Emissions	Sums all annual LDV emission sources to report a transportation wide value, similar to that reported in EIAs *Annual Energy Outlook*.	Fuel and Emissions
Annual Liquid Fuel Consumption	Annual Liquid Fuel Consumption	A flow variable that represents the annual consumption of liquid fuel.	Fuel and Emissions
Annual Scrapped Vehicles	Annual Scrapped Vehicles	Calculates annual number of vehicles scrapped across all model cohorts. Used as an input in new vehicle purchases.	Cohort, Consumer
Annual VC Grid Electricity Emissions	Annual Vehicle Class Electricity Emissions	Calculates annual grid electricity emissions by vehicle class.	Calculations
Annual VC Liquid Fuel Consumption	Annual Vehicle Class Liquid Fuel Consumption	Calculates annual liquid fuel consumption by vehicle class.	Calculations

Variable *(alphabetical)*	Full Name	Description	Subsystem(s)
Annual VC Scrapped Vehicles	Annual Vehicle Class Scrapped Vehicles	Calculates annual number of scrapped vehicles by class.	Cohort
Annual VC Tailpipe Emissions	Annual Tailpipe Emissions by Vehicle Class	Calculates annual tailpipe emissions by class.	Calculations
Annual VC Transportation Emissions	Annual Vehicle Class Transportation Emissions	Calculates annual total emissions by vehicle class.	Calculations
Annual VC Upstream Fuel Emissions	Annual Vehicle Class Upstream Fuel-related Emissions	Calculates annual upstream fuel emissions by class.	Calculations
Annual VC VP	Annual Vehicle Class Population	Calculates the annual in use vehicle population by class.	Calculations
Annual VCVT Grid Electricity Consumption	Annual Vehicle Class/Vehicle Fuel Type Grid Electricity Consumption	Calculates annual grid electricity consumption by vehicle class/vehicle fuel type.	Fuel and Emissions
Annual VCVT Grid Electricity Emissions	Annual Vehicle Class/Vehicle Fuel Type Grid Electricity Emissions	Calculates annual grid electricity emissions by vehicle class/vehicle fuel type.	Fuel and Emissions
Annual VCVT Scrapped Vehicles	Annual Vehicle Class/Vehicle Fuel Type Scrapped Vehicles	Calculates annual number of vehicle class/vehicle fuel types scrapped.	Cohort
Annual VCVT Tailpipe Emissions	Annual Vehicle Class/Vehicle Fuel Type Tailpipe Emissions	Calculates annual tailpipe emissions by vehicle class/vehicle fuel type.	Fuel and Emissions
Annual VCVT Transportation Emissions	Annual Vehicle Class/Vehicle Fuel Type Transportation Emissions	Calculates annual total emissions by vehicle class/vehicle fuel type.	Fuel and Emissions
Annual VCVT Upstream Fuel Emissions	Annual Vehicle Class/Vehicle Fuel Type Upstream Fuel Emissions	Calculates annual upstream fuel emissions by vehicle class/vehicle fuel type.	Fuel and Emissions
Annual VCVT VMT	Annual Vehicle Class/Vehicle Fuel Type Miles Traveled	Calculates annual VMT by vehicle class/vehicle fuel type populations.	Calculations
Annual VCVT VP	Annual Vehicle Class/Vehicle Fuel Type Population	Calculates annual vehicle class/vehicle fuel type populations.	Calculations
Annual VMT Change EX	Exogenous Annual Change in Vehicle Miles Travel	A growth variable that allows users to input an exogenous percent change in annual VMT. Used to parameterize macroeconomic and cultural trends similar to those used by AEO.	Cohort
Annual VT Grid Electricity Emissions	Annual Vehicle Fuel Type Grid Electricity Emissions	Calculates annual grid electricity emissions by vehicle fuel type.	Calculations
Annual VT Liquid Fuel Consumption	Annual Vehicle Fuel Type Liquid Fuel Consumption	Calculates annual liquid fuel consumption by vehicle fuel type.	Calculations
Annual VT Scrapped Vehicles	Annual Vehicle Fuel Type Scrapped Vehicles	Calculates annual number of scrapped vehicles by vehicle fuel type.	Cohort
Annual VT Tailpipe Emissions	Annual Tailpipe Emissions by Vehicle Fuel Type	Calculates annual tailpipe emissions by vehicle fuel type.	Calculations
Annual VT Transportation Emissions	Annual Vehicle Fuel Type Transportation Emissions	Calculates total annual emissions by vehicle fuel type.	Calculations
Annual VT Upstream Fuel Emissions	Annual Vehicle Fuel Type Upstream Fuel Emissions	Calculates annual upstream fuel emissions by vehicle fuel type.	Calculations

Variable *(alphabetical)*	Full Name	Description	Subsystem(s)
Annual VT VP	Annual Vehicle Fuel Type Populations	Calculates annual vehicle fuel type populations.	Calculations
At Generalized Cost	Vehicle Price Slope Generalized Cost Value	Model constant for computing vehicle price slope.	Consumer
At Market Share	Vehicle Price Slope Market Share Value	Model constant for computing vehicle price slope.	Consumer
At Market Value	Fuel Choice Price Slope Market Value	Model constant for computing fuel choice price slope.	Consumer
Available Scrapped Vehicles	Available Scrapped Vehicles	A flow variable that simulates the use of scrapped vehicles for material recycling purposes. Model currently doesn't support a material production submodel, so the variable is disabled.	Cohort
B EXP Uk	Battery Technology Utility Exponent	Calculates the exponent of consumer utility for battery -independent vehicle technology.	Consumer
B LN SUM EXP	Battery Technology Normalized Utility	Calculates average consumer utility for battery -independent vehicle technology.	Consumer
B SUM EXP	Sum of Battery Technology Vehicle Utility	Calculates the sum of the exponential for all consumer utilities for battery-independent vehicle technology. Note, current model structure only includes PHEV in this category.	Consumer
B Tech Type Share	Battery Technology Vehicles Market Share	Calculates market share of battery-independent vehicle technology.	Consumer
B Uk	Battery Technology Vehicles Consumer Utility	Calculates consumer utility for battery-independent vehicle technology.	Consumer
B VCVT Shares	Unweighted Market Shares for Battery-Independent Technology Vehicles	Calculates the unweighted market share for battery-independent vehicle technology.	Consumer
Baseline Fuel Availability	Baseline Fuel Availability	Initial fractional availability of each fuel type.	Producer
Baseline Fuel Economy	Baseline New Vehicle Fuel Economy	Exogenous variable that represents the new vehicle fuel economy for the initial time increment.	Cohort, Consumer, Producer
Baseline Grid Electricity Price	Baseline Grid Electricity Price	User input values that provide the initial price of electricity as published in the EIA Annual Energy Outlook.	Consumer
Baseline Liquid Fuel Price	Baseline Liquid Fuel Price	User input values that provide initial liquid fuel prices (i.e. gasoline, diesel, and E85) as published in the EIA Annual Energy Outlook.	Consumer
Baseline Maintenance Cost	Baseline New Vehicle Maintenance Cost	Exogenous variable that represents the annual maintenance cost for the initial time increment.	Consumer, Producer
Baseline Make/Model Availability	Baseline Make/Model Availability	Initial number of make/models available for purchase for each vehicle fuel type.	Producer
Baseline New Vehicle Retail Price	Baseline New Vehicle Retail Price	Exogenous variable used to represent the new vehicle retail price, before subsidies or taxes, for the initial time increment.	Producer
Baseline Range	Baseline New Vehicle Range	Exogenous variable used that represents the new vehicle range for the initial time increment.	Producer
Beta Normalized VMT Difference	Beta Normalized Vehicle Miles Traveled Difference	Calculates the rate at which scrappage rates will change as values near the *Median Accumulated VMT*.	Cohort
C EXP Uk	Conventional Technology Utility Exponent	Calculates the exponent of consumer utility for conventional technology vehicles.	Consumer
C LN SUM EXP	Conventional Technology Normalized Utility	Calculates the average consumer utility for conventional vehicle technology vehicles.	Consumer
C SUM EXP	Sum of Conventional Technology Vehicle Utility	Calculates the sum of the exponential for all consumer utilities for conventional technology vehicles. Note, current model structure only includes gasoline, hybrid electric, diesel, and flex fuel vehicles in this category.	Consumer
C Tech Type Share	Conventional Technology Vehicles Market Share	Calculates the market share of conventional technology vehicles.	Consumer

Variable *(alphabetical)*	Full Name	Description	Subsystem(s)
C Uk	Conventional Technology Consumer Utility	Calculates the consumer utility for conventional technology vehicles.	Consumer
C VCVT Shares	Unweighted Market Shares for Conventional Technology Vehicles	Calculates the unweighted market share for conventional vehicle technology new purchases.	Consumer
Carbon Fraction of Fuel	Carbon Fraction of Fuel	Model constant that represents the amount of carbon in a kilogram of fuel.	Fuel and Emissions
Carbon Per Gallon of Fuel	Tons of Carbon Per Gallon of Fuel	Model constant that represents the amount of carbon produced by burning a gallon of fuel.	Fuel and Emissions
Carbon Per kWh	Carbon Per Kilowatt-hour	Model constant that represents the amount of carbon produced per a kilowatt-hour of electricity from the grid.	Fuel and Emissions
Carbon Tax	Carbon Tax	Variable representation of a carbon tax policy.	Consumer
CE Acceleration	Acceleration Coefficient	Consumer submodel constant used in utility function calculation.	Consumer
CE FE MCC 1	Fuel Economy Marginal Cost Curve Equation Coefficient 1	Marginal cost curve coefficient, a_1.	Producer
CE FE MCC 2	Fuel Economy Marginal Cost Curve Equation Coefficient 2	Marginal cost curve coefficient, a_2.	Producer
CE Fuel Availability 1	Fuel Availability Coefficient 1	Consumer submodel constant used in utility function calculation.	Consumer
CE Fuel Availability 2	Fuel Availability Coefficient 2	Consumer submodel constant used in utility function calculation.	Consumer
CE Fuel Cost	Fuel Cost Coefficient	Consumer submodel constant used in utility function calculation.	Consumer
CE Home Refueling for EVs	Home Refueling for EVs Coefficient	Consumer submodel constant used in utility function calculation.	Consumer
CE Luggage Space	Luggage Space Coefficient	Consumer submodel constant used in utility function calculation.	Consumer
CE Maintenance Cost	Maintenance Cost Coefficient	Consumer submodel constant used in utility function calculation.	Consumer
CE Make/Model Availability	Make/Model Availability Coefficient	Consumer submodel constant used in utility function calculation.	Consumer
CE Multifuel Capability	Multifuel Capability Coefficient	Consumer submodel constant used in utility function calculation.	Consumer
CE Range	Range Coefficient	Consumer submodel constant used in utility function calculation.	Consumer
CE Top Speed	Top Speed Coefficient	Consumer submodel constant used in utility function calculation.	Consumer
CE Vehicle Price	Vehicle Price Coefficient	Consumer submodel constant used in utility function calculation.	Consumer
Change in FC Per Mile	Change in Fuel Cost Per Mile	Calculates the annual change in fuel cost per mile for each vehicle class/vehicle fuel type.	Consumer
Change in Fuel Economy	Change in Fuel Economy	Calculates the annual percent change in fuel economy for each vehicle class/fuel type.	Producer
Change in Grid Electricity Price	Change in Grid Electricity Price	Inputs the annual change in the price of electricity.	Consumer
Change in Liquid Fuel Price	Change in Liquid Fuel Price	Inputs the annual change in the price of liquid fuels (i.e. gasoline, diesel, and E85).	Consumer
Change in Vehicle Price EX	Exogenous New Vehicle Price Change	Exogenous variable used to simulate the annual change in new vehicle prices.	Producer
Change in Vehicle Price FE	Change in Vehicle Price due to Change in Fuel Economy	Calculates the change in new vehicle price due to the annual change in new vehicle fuel economy.	Producer
Change in VMT FC	Change in Vehicle Miles Traveled Due to Fuel Cost	Calculates the change in VMT due to the change in fuel cost per mile.	Consumer

Variable *(alphabetical)*	Full Name	Description	Subsystem(s)
Consumer Utility	Vehicle Class/Vehicle Fuel Type Consumer Utility	Calculates the sum of the product of all vehicle class/vehicle fuel type attributes and coefficients, given that VCVT Switch allows market penetration. Vehicle attribute coefficients are prefixed 'CE'; vehicle coefficient/attribute products are prefixed 'P'; vehicle attributes are explicitly titled.	Consumer
Consumer Utility of Fuels	Consumer Utility of Fuels	Calculates the consumer utility of choosing gasoline and E85. Fuel attribute are fuel cost, vehicle range, and fuel availability, denoted by 'F'. Fuel cost takes into account a vehicles fuel economy. A generalized equation is given.	Consumer
Conversion of C to CO2	Conversion of Carbon to Carbon Dioxide	A conversion variable that translates carbon to carbon dioxide.	Fuel and Emissions
Density of Fuel	Density of Fuel	A model constant that represents the density of the fuel mix.	Fuel and Emissions
E Sum Weighted Mean	Electric Grid Dependent Vehicle Population Sum Weighted Mean Fuel Economy	Calculates the electric-based fuel economy, weighted by population, for all battery-independent vehicles in use (i.e. PHEV).	Consumer
E Weighted Mean Conversion	Electric Grid Dependent Vehicle Cohorts Weighted Mean Fuel Economy	Calculates the electric-based fuel economy, weighted by cohort, for all battery-independent vehicles in use (i.e. PHEV).	Consumer
E Weighted Mean mpkWh	Electric Grid Dependent Vehicle Population Weighted Mean Fuel Economy	Calculates the electric-based fuel economy, weighted by population, for battery-independent vehicles (i.e. PHEV).	Consumer
Elasticity of Vehicle Tech	Elasticity of Vehicle Technology to Price	Model constant for computing the vehicle price slope.	Consumer
Elasticity of VMT FC Per Mile	Elasticity of Vehicle Miles Traveled to Fuel Cost Per Mile	Model constant for computing the marginal change in VMT to the marginal change in fuel cost per mile.	Consumer
EPA Degradation Factor	EPA Fuel Economy Degradation Factor	A model constant that represents the difference, or degradation, of the reported fuel economy of each vehicle class/vehicle fuel type and their actual value under real driving conditions.	Cohort
EXP Consumer Utility of Fuels	Exponential of Consumer Utility of Fuels	Calculates the exponential of the consumer utility of gasoline and E85. A generalized equation is shown.	Consumer
EXP Normalized VMT Difference	Exponent of Normalized Vehicle Miles Traveled Difference	Calculates the exponent of *Beta Normalized VMT Difference*.	Cohort
F Fuel Availability	Fuel Choice Model Availability Attribute	Calculates the utility for fuel availability, to be used in the fuel choice submodel, for each vehicle class/vehicle fuel types.	Consumer
F Fuel Cost	Fuel Choice Model Cost Attribute	Calculates the utility for fuel cost, to be used in the fuel choice submodel, for each vehicle class/vehicle fuel type.	Consumer
F Range	Fuel Choice Model Vehicle Range Attribute	Calculates the utility for range, to be used in the fuel choice submodel, for each vehicle class/vehicle fuel type.	Consumer
FC Per Mile	Fuel Cost Per Mile	Calculates the fuel cost per mile for the current time step using the population weighted average fuel economy of each vehicle fuel type set.	Consumer
Fuel Availability	Fuel Availability	Inputs the fractional availability of each fuel type compared to gasoline (=1).	Consumer
Fuel Availability Growth	Fuel Availability Growth	Exogenous variable used to simulate the annual change of the availability of each fuel type.	Producer
Fuel Choice Attribute Value	Vehicle Class/Vehicle Fuel Type Fuel Choice Attribute Value	Calculates the fuel choice attribute for FFVs. The current model only calculates fuel choice for gasoline and E85.	Consumer
Fuel Choice Elasticity	Fuel Choice Elasticity	Model constant that represents the marginal change in probability of choosing gasoline or E85 compared to the change in fuel price.	Consumer

Variable *(alphabetical)*	Full Name	Description	Subsystem(s)
Fuel Choice Price Slope	Fuel Choice Price Slope	Calculates the price slope for choosing among different fuels.	Consumer
Fuel Cost	Vehicle Class/Vehicle Fuel Type Fuel Cost	Calculates the gallon of gasoline equivalent fuel cost for each vehicle class/vehicle fuel type in use. Each vehicle type equation is dependent on fuel mix, so a general equation is given.	Consumer
Fuel Cost Per GGE	Fuel Cost Per Gallon of Gasoline Equivalent Energy Content	Calculates the cost of a gallon of fuel per its energy content and normalized to a gallon of gasoline.	Consumer
Fuel Economy	New Vehicle Fuel Economy	Inputs the fuel economy for new vehicles. Can either be a lookup table or direct user input.	Producer
Fuel Economy Growth CAFÉ	Fuel Economy Standard Annual Change	User input variable representing the annual change in vehicle class/fuel type fuel economy due to a fuel economy standard.	Consumer, Producer
Fuel Economy Growth EX	Exogenous New Vehicle Fuel Economy Growth	Exogenous variable used to allow users to simulate an annual change in new vehicle fuel economy.	Cohort, Consumer, Producer
Fuel Energy Content	Fuel Energy Content	Model constants for the energy content of each fuel type. Model currently addresses gasoline, diesel, electricity, and E85.	Consumer
Fuel Tax	Fuel Tax	Calculates the tax on fuel due to a carbon tax policy.	Consumer
Historical VCVT Fuel Economy	Historical Vehicle Class/Vehicle Fuel Type Fuel Economy	A lookup table that represents the model cohort fuel economy for the initial vehicle populations per vehicle class/vehicle fuel type.	Cohort
Home Refueling for EVs	Home Refueling for Electric-dependent Technology Vehicles	Inputs whether a vehicle class/vehicle fuel type can be plugged in at home to recharge (0 = No; 1 = Yes).	Producer
Initial Model Year Accumulated VMT	Initial Model Year Accumulated Vehicle Miles Traveled	Calculates the accumulated VMT for each VC/VT cohort based on *Initial Model Year Accumulated VMT*. Provides a baseline accumulated VMT.	Cohort
Initial Model Year VMT	Initial Model Year Vehicle Miles Traveled	Inputs the initial model cohort VMT. Used as a baseline for the first model time step.	Cohort
Initial Vehicle Population Inputs	Initial Vehicle Population Inputs	Inputs the initial model cohort vehicle populations, by vehicle class/vehicle fuel type. Cohorts range from 1 to 20 (i.e. 1986-2006).	Cohort
Initial Vehicle Population Switch	Initial Vehicle Population Switch	Variable calculates the time step vehicle technologies enter the market. Allows for the forced market penetration of vehicle technologies for different scenarios.	Cohort
kg of Fuel Per Year	Kilograms of Fuel Consumed Per Year	Calculates the mass of liquid fuel consumed annual.	Fuel and Emissions
LF SUM Weighted Mean	Liquid Fuel Vehicle Population Sum Weighted Mean Fuel Economy	Calculates the liquid fuel economy, weighted by population, for all liquid fuel vehicles in use (i.e. gasoline, diesel, HEV, and FFVs).	Consumer
LF Weighted Mean Conversion	Liquid Fuel Vehicle Cohorts Weighted Mean Fuel Economy	Calculates the liquid fuel economy, weighted by cohort, for all liquid fuel vehicles in use (i.e. gasoline, diesel, HEV, and FFVs).	Consumer
LF Weighted Mean MPG	Liquid Fuel Vehicle Population Weighted Mean Fuel Economy	Calculates the liquid fuel economy, weighted by population, for liquid vehicles (i.e. gasoline, diesel, HEV, and FFVs).	Consumer
Luggage Space	Luggage Space	Inputs the luggage space for each vehicle class/vehicle fuel type.	Producer
Maintenance Cost	Maintenance Cost	Inputs the annual maintenance cost of each vehicle class/vehicle fuel type.	Producer
Maintenance Cost Growth	New Vehicle Maintenance Cost Growth	Exogenous variable used to allow users to simulate an annual change in new vehicle maintenance costs.	Consumer, Producer
Make/Model Availability	Vehicle Make/Model Availability	Inputs the number of available make and models for each vehicle class/vehicle fuel type.	Producer
Make/Model Availability Growth	Make/Model Availability Growth	Exogenous variable used to simulate the annual change of the number of make/models available for each vehicle fuel type.	Producer

Variable *(alphabetical)*	Full Name	Description	Subsystem(s)
Median Accumulated VMT	Median Accumulated Vehicle Miles Traveled	The accumulated VMT value where scrappage rates for that cohort reaches 50%. It is used to calibrate the scrappage rate equation.	Cohort
Multifuel Capability	Multifuel Capability	Inputs whether a vehicle class/vehicle fuel type is capable of using multiple fuels (0 = No; 1 = Yes).	Producer
New Vehicle Retail Price	New Vehicle Retail Price	Inputs the baseline, retail price for new vehicle class/vehicle fuel types.	Producer
Normalized VMT Difference	Normalized Vehicle Miles Traveled Difference	Calculates the normalized VMT difference between each VC/VT cohort and the *Median Accumulated VMT*.	Cohort
Old FC Per Mile	Fuel Cost Per Mile from Previous Year	Calculates the fuel cost per mile from the previous time step. A delay function is used to lag the calculation, thus allowing the annual difference to be calculated.	Consumer
Old Fuel Economy	Old Fuel Economy	Used to store fuel economy values from t-1 to calculate the annual change.	Producer
Old Vehicle Cohort Accumulated VMT	Old Vehicle Cohort Accumulated Vehicle Miles Traveled	Accumulates VMT for each VC/VT cohort through the *previous* time step.	Cohort
P Acceleration	Acceleration Product	Calculates the product of the vehicle attribute and the consumer utility function coefficient.	Consumer
P Fuel Availability	Fuel Availability Product	Calculates the product of the vehicle attribute and the consumer utility function coefficient.	Consumer
P Fuel Cost	Fuel Cost Product	Calculates the product of the vehicle attribute and the consumer utility function coefficient.	Consumer
P Home Refueling for EVs	Home Refueling for EVs Product	Calculates the product of the vehicle attribute and the consumer utility function coefficient.	Consumer
P Luggage Space	Luggage Space Product	Calculates the product of the vehicle attribute and the consumer utility function coefficient. Luggage space for each vehicle class/vehicle fuel type is calculated as a fraction of its gasoline vehicle counterpart.	Consumer
P Maintenance Cost	Maintenance Cost Product	Calculates the product of the vehicle attribute and the consumer utility function coefficient.	Consumer
P Make/Model Availability	Make/Model Availability Product	Calculates the product of the vehicle attribute and the consumer utility function coefficient. Make/Model Availability for each vehicle class/vehicle fuel type is calculated as a fraction of its gasoline vehicle counterpart.	Consumer
P Multifuel Capability	Multifuel Capability Product	Calculates the product of the vehicle attribute and the consumer utility function coefficient.	Consumer
P Range	Range Product	Calculates the product of the vehicle attribute and the consumer utility function coefficient.	Consumer
P Top Speed	Top Speed Produce	Calculates the product of the vehicle attribute and the consumer utility function coefficient.	Consumer
P Vehicle Price	Vehicle Price Product	Calculates the product of the vehicle attribute and the consumer utility function coefficient.	Consumer
PHEV Electric Fuel Economy	PHEV Electric Fuel Economy	Inputs the fuel economy for new PHEV entering the market.	Producer
Probability of Fuel Choice	Probability of Fuel Choice	Calculates the probability of choosing either gasoline or E85 for all FFVs in use.	Consumer
Purchases by VC	New Vehicle Purchases by Vehicle Class	Calculates the number of new vehicles to be purchased by vehicle class.	Consumer
Range	Range	Inputs the range each vehicle class/vehicle fuel type can reach on one fueling.	Producer
Range Growth	New Vehicle Range Growth	Exogenous variable used to simulate an annual change in new vehicle range.	Producer
Rebound Effect Switch	Rebound Effect Switch	A switch that allows users to turn the rebound effect feedback ‘on’ or ‘off’.	Cohort

Variable *(alphabetical)*	Full Name	Description	Subsystem(s)
Relative Fuel Cost	Relative Fuel Cost	Calculates the cost of driving either with gasoline or E85. This cost then is used to calculate the share of driving either when using a FFV.	Consumer
Relative MPG	Relative Miles Per Gallon Conversion	Model constants that normalize vehicle fuel economy across technology types.	Consumer
Scrappage Alpha	Scrappage Model Constant	A model constant used in the scrappage rate equation.	Cohort
Scrappage Beta	Beta Constant of Scrappage Rate Equation	The scrappage growth rate constant that represents the rate of change in scrappage as values near the *Median Accumulated VMT*.	Cohort
Scrappage Rate	Scrappage Rate	Calculates the model cohort scrappage rate, dependent on the *Retirement Growth Rate*.	Cohort
Scrappage-VMT Feedback Switch	Vehicle Scrappage-Vehicle Miles Traveled Feedback Switch	A switch that allows users to turn the Scrappage-VMT feedback 'on' or 'off'.	Cohort
Scrapped Vehicles	Scrapped Vehicles	A flow variable that represents the number of vehicles scrapped from each model cohort annually.	Cohort
Scrapped Vehicles Stock	Scrapped Vehicles Stock	A stock variable that represents the total number of scrapped vehicles available from the vehicle population.	Cohort
Stock Conversion	Stock Conversion	A variable used to convert text based model cohort titles to numerical titles for use in calculations.	Cohort
SUM EXP Consumer Utility of Fuels	Sum of Exponential Consumer Utility of Fuels	Calculates the sum of consumer utility for gasoline and E85.	Consumer
SUM EXP Uk	Sum of Vehicle Technology Utility Exponents	Calculates the sum of battery-independent and conventional vehicle technology utility exponents. Used for calculating the market share of each vehicle technology set.	Consumer
Taxed Fuel Price	Taxed Fuel Price	Calculates the retail, taxed fuel price for each fuel type.	Consumer
Taxed Vehicle Price	Taxed Vehicle Price	Calculates the retail price of each vehicle class/fuel type given any tax or subsidies implemented due to policy changes.	Consumer, Producer
Top Speed	Top Speed	Inputs the top speed each vehicle class/vehicle fuel type can reach.	Producer
Total LDV Emissions	Total Light Duty Vehicle Emissions	Calculates total LDV emissions from all fuels and vehicles over all time steps.	Fuel and Emissions
Total New Sales	Total New Vehicle Sales	Calculates total LDV emissions from all fuels and vehicles over all time steps.	Consumer
Total VC Scrapped Vehicles	Total Scrapped Vehicles by Class	Calculates the total number of scrapped vehicles over all time steps by vehicle class.	Calculations
Total VC VMT	Total Vehicle Class Miles Traveled	Calculates total VMT over all time steps by vehicle class.	Calculations
Total VC VP	Total Vehicle Class Population	Calculates total vehicle population over all time steps by vehicle class.	Calculations
Total VCVT Grid Electricity Consumption	Total Vehicle Class/Vehicle Fuel Type Grid Electricity Consumption	Calculates total grid electricity consumption over all time steps by vehicle class/vehicle fuel type.	Fuel and Emissions
Total VCVT Grid Electricity Emissions	Total Vehicle Class/Vehicle Fuel Type Grid Electricity Emissions	Calculates total grid electricity emissions over all time steps by vehicle class/vehicle fuel type.	Fuel and Emissions
Total VCVT Liquid Fuel Consumption	Total Vehicle Class/Vehicle Fuel Type Liquid Fuel Consumption	Calculates total liquid fuel consumption for each vehicle class/vehicle fuel type over all time steps.	Fuel and Emissions
Total VCVT Tailpipe Emissions	Total Vehicle Class/Vehicle Fuel Type Tailpipe Emissions	Calculates total tailpipe emissions produced over all time steps by vehicle class/vehicle fuel type.	Fuel and Emissions
Total VCVT Transportation Emissions	Total Vehicle Class/Vehicle Fuel Type Transportation Emissions	Calculates total vehicle class/vehicle fuel type emissions from all fuels and vehicles over all time steps.	Fuel and Emissions

Variable *(alphabetical)*	Full Name	Description	Subsystem(s)
Total VCVT Upstream Fuel Emissions	Total Vehicle Class/Vehicle Fuel Type Upstream Fuel Emissions	Calculates total upstream fuel emissions over all time steps by vehicle class/vehicle fuel type.	Fuel and Emissions
Total VCVT VMT	Total Vehicle Class/Vehicle Fuel Type Miles Traveled	Calculates total VMT over all time steps by vehicle class/vehicle fuel type.	Cohort
Total VCVT VP	Total Vehicle Class/Vehicle Fuel Type Population	Calculates total vehicle population over all time steps by vehicle class/vehicle fuel type.	Calculations
Total VMT	Total Vehicle Class/Vehicle Fuel Type Miles Traveled	Calculates total VMT for all vehicles over all time steps.	Calculations
Total VT Scrapped Vehicles	Total Scrapped Vehicles by Type	Calculates the total number of scrapped vehicles produced over all time steps by vehicle fuel type.	Calculations
Total VT VMT	Total Vehicle Fuel Type Miles Traveled	Calculates total VMT over all time steps by vehicle fuel type.	Calculations
Total VT VP	Total Vehicle Fuel Type Populations	Calculates total vehicle population over all time steps by vehicle fuel type.	Calculations
Untaxed Fuel Price	Untaxed Fuel Price	Calculates the before retail, untaxed fuel price. It is assumed that changes are due to market trends, which are captured in the user inputted *Change in Liquid Fuel Price* variable.	Consumer
Untaxed Vehicle Price	Vehicle Price	Calculates the final vehicle price for new purchases based on retail price, taxes, and subsidies.	Producer
Upstream Emissions Factor	Upstream Emissions Factor	Sums both individual upstream fuel emissions factors into on conversion variable.	Fuel and Emissions
Upstream Feedstock Emissions Factor	Upstream Feedstock Emissions Factor	Inputs feedstock emissions factors for each vehicle class/vehicle fuel type. Data was taken from DOE GREET model.	Fuel and Emissions
Upstream Fuel Emissions Factor	Upstream Fuel Emissions Factor	Inputs fuel emissions factors for each vehicle class/vehicle fuel type. Data was taken from DOE GREET model.	Fuel and Emissions
VC New Consumer Vehicle Purchases	New Consumer Vehicle Purchases by Vehicle Class (True Value)	Translates new consumer purchases by vehicle class.	Calculations
VC Shares	Vehicle Class Market Shares	Inputs the market share of each vehicle class. This variable acts as a parameterization in absence of a macroeconomic model needed to endogenously calculate class shares.	Consumer
VCVT Carbon Consumption Per Fuel	Vehicle Class/Vehicle Fuel Type CO_2 Emissions Per Fuel	Calculates the carbon dioxide emissions produced annually per fuel.	Fuel and Emissions
VCVT EXP	Vehicle Class/Vehicle Fuel Type Consumer Utility Exponent	Calculates the exponent of each vehicle class/vehicle fuel type consumer utility value.	Consumer
VCVT Grid Electricity Consumption	Vehicle Class/Vehicle Fuel Type Grid Electricity Consumption	Calculates grid electricity consumption by vehicle class/vehicle fuel type.	Fuel and Emissions
VCVT Liquid Fuel Consumption	Vehicle Class/Vehicle Fuel Type Liquid Fuel Consumption	Calculates liquid fuel consumption by vehicle class/vehicle fuel type.	Fuel and Emissions
VCVT New Consumer Vehicle Purchases	New Consumer Purchases by Vehicle Class/Vehicle Fuel Type	Calculates the number of new vehicle class/vehicle fuel types to be purchased annually.	Consumer
VCVT Switch	Vehicle Class/Vehicle Fuel Type Switch	Variable acts as an 'on/off' switch for each vehicle class/vehicle fuel type over time. Allows model scenarios to be built by forcing or hindering the penetration of different vehicle types and sizes.	Cohort, Consumer
Vehicle Cohort Accumulated VMT	Current Time Step Vehicle Cohort Accumulated Vehicle Miles Traveled	Accumulates VMT for each VC/VT cohort through the *current* time step.	Cohort

Variable *(alphabetical)*	Full Name	Description	Subsystem(s)
Vehicle Cohort VMT	Vehicle Stock Miles Traveled	A stock variable that represents the miles traveled per vehicle per vehicle cohort.	Cohort
Vehicle Purchases	Vehicle Purchases	A flow variable that represents the entrance of new vehicles into the population.	Cohort
Vehicle Stock Cohorts	Vehicle Stock Cohorts	A stock variable that represents all vehicle population cohorts, through 20 years old, for all vehicle class/vehicle fuel types.	Cohort
Vehicle Stock Fuel Economy	Vehicle Stock Fuel Economy	Allocates fuel economy for each vehicle class/vehicle fuel type and each cohort. Uses *Historical VCVT Fuel Economy* and *Fuel Economy*.	Cohort
Vehicle Stock Grid Electricity Consumption	Vehicle Stock Grid Electricity Consumption	Calculates the grid electricity consumption by vehicle cohort.	Fuel and Emissions
Vehicle Stock Liquid Fuel Consumption	Vehicle Stock Liquid Fuel Consumption	Calculates liquid fuel consumption by vehicle cohort.	Fuel and Emissions
Vehicle Stock VMT	Vehicle Stock Miles Traveled	Calculates VMT for each model cohort.	Cohort
Vehicle Stock VMT Per Fuel	Vehicle Stock Miles Traveled Per Fuel Type	Calculates VMT for each model cohort by fuel type.	Cohort, Fuel and Emissions
Vehicle Subsidies	Vehicle Subsidies	Inputs any government subsidies (or tax, if set to negative) implemented due to public policies on vehicle class/vehicle fuel types.	Producer
VMT Normalization Constant	Vehicle Miles Traveled Normalization Constant	Value used to calibrate the scrappage rate equation. Normalizes the difference in accumulated VMT.	Cohort
VT New Consumer Vehicle Purchases	New Consumer Vehicle Purchases by Vehicle Fuel Type	Calculates new vehicle purchases by vehicle fuel type.	Calculations
VT PofP	Probability of Purchasing Vehicle Fuel Types	Calculates the probability consumers will purchase each vehicle fuel type.	Consumer
VT Price Slope	Vehicle Fuel Type Price Slope	Calculates the price slope for vehicle technologies.	Consumer
VT Sales Market Share	Vehicle Fuel Type Market Share of New Sales	Calculates the annual market share of new sales by vehicle fuel types	Consumer
Year Conversion	Year Conversion	Conversion variable that translates model time steps into years. For use in determining market penetration of new vehicle technologies.	Cohort, Consumer
Year Fuel Economy Standard Met	Year Fuel Economy Standard Met	User input variable representing the year manufacturers must meet a fuel economy standard.	Consumer, Producer
Year Subsidies End	Year New Vehicle Subsidies Expire	User input variable representing the year a vehicle subsidy policy expires.	Consumer, Producer

Appendix 2.2 CLIMATS Model Variables, Subscripts, Units and Equations

Variable *(alphabetical)*	Subscripts	Units	Equation	User Input ?
% Driven on Gasoline	VC, VT	percent	**User input constants**	No
% Use of Fuel	VC, VT, SY, FT	percent	**Vehicle Fuel Type dependent IF statements**	No
Acceleration	VC, VT	seconds	**User input constants**	Yes
Aging Vehicles	VC, VT, SY	vehicles	$= (\boldsymbol{Vehicle\ Stock\ Cohorts}) - (\boldsymbol{Scrapped\ Vehicles})$	No
Annual Change in Fuel Availability	VC, VT	fraction	$= (\boldsymbol{Fuel\ Availability_{t-1}}) * (\boldsymbol{Fuel\ Availability\ Growth})$	No
Annual Change in Fuel Economy	VC, VT	Miles per gallon	$= (\boldsymbol{Fuel\ Economy})_{t-1} * (\boldsymbol{Fuel\ Economy\ Growth})$	No
Annual Change in Maintenance Cost	VC, VT	\$(2007)	$= (\boldsymbol{Maintenance\ Cost})_{t-1} * (\boldsymbol{Maintenance\ Cost\ Growth})$	No
Annual Change in Make/Model Availability	VC, VT	models	$= (\boldsymbol{Make - Model\ Availability_{t-1}}) * (\boldsymbol{Make - Model\ Availability\ Growth})$	No
Annual Change in Range	VC, VT	miles	$= (\boldsymbol{Range})_{t-1} * (\boldsymbol{Range\ Growth})$	No
Annual Change in Sales	---	percent	**User input constant**	Yes
Annual Change in Untaxed Fuel Price	FT	\$/gallon	$= (\boldsymbol{Untaxed\ Fuel\ Price})_{t-1} * (\boldsymbol{Change\ in\ Fuel\ Price})$ **Where, *Change in Fuel Price* is represented by *Change in Liquid Fuel Price* and *Change in Electricity Grid Price*.**	No
Annual Change in Vehicle Price	VC, VT	\$(2007)	$= (\boldsymbol{Vehicle\ Price})_{t-1} * (\boldsymbol{Vehicle\ Price\ Growth}) - (\boldsymbol{Vehicle\ Subsidies})$	No
Annual Change in VMT	VC, VT, SY	miles	$= (\boldsymbol{Annual\ VMT\ Change\ EX}) + [(\boldsymbol{Annual\ VMT\ Change\ FC}) * (\boldsymbol{Rebound\ Effect\ Switch})]$ **Where, *Scrappage-VMT Feedback Switch* is 0 if feedback is turned off and is 1 if feedback is turned on.**	No
Annual Growth in VMT	---	percent	**User input constant**	Yes
Annual LDV Emissions	---	million metric tons	$= \sum_{VC} (\boldsymbol{Annual\ VC\ Transportation\ Emissions})$	No
Annual Liquid Fuel Consumption	VC, VT, FT	gallons	$= (\boldsymbol{Total\ VCVT\ Fuel\ Consumption})$	No
Annual Scrapped Vehicles	---	vehicles	$= \sum_{VC} (\boldsymbol{Annual\ VC\ Scrapped\ Vehicles})$	No
Annual VC Grid Electricity Emissions	VC, VT	million metric tons	$= \sum_{VT} (\boldsymbol{Annual\ VCVT\ Grid\ Electricity\ Emissions})_{\boldsymbol{Electricity}}$	No
Annual VC Liquid Fuel Consumption	VC, FT	gallons	$= \sum_{VC} (\boldsymbol{Annual\ Liquid\ Fuel\ Consumption})$	No
Annual VC Scrapped Vehicles	VC	vehicles	$= \sum_{VT} (\boldsymbol{Annual\ VCVT\ Scrapped\ Vehicles})$	No

Variable *(alphabetical)*	Subscripts	Units	Equation	User Input ?
Annual VC Tailpipe Emissions	VC	million metric tons	$= \sum_{VT} (\boldsymbol{Annual\ VCVT\ Transportation\ Emissions})$	No
Annual VC Transportation Emissions	VC	million metric tons	$= \sum_{VT} (\boldsymbol{Annual\ VCVT\ Transportation\ Emissions})$	No
Annual VC Upstream Fuel Emissions	VC	million metric tons	$= \sum_{VT} (\boldsymbol{Annual\ VCVT\ Upstream\ Fuel\ Emissions})$	No
Annual VC VP	VC	vehicles	$= \sum_{VT} (\boldsymbol{Annual\ VCVT\ VP})$	No
Annual VCVT Grid Electricity Consumption	VC, VT, FT	kWh	$= (\boldsymbol{VCVT\ Grid\ Electricity\ Consumption})$	No
Annual VCVT Grid Electricity Emissions	VC, VT, FT	million metric tons	$= \frac{(\boldsymbol{Annual\ VCVT\ Grid\ Electricity\ Emissions}) * (\boldsymbol{Carbon\ Per\ kWh})}{\boldsymbol{1e6}}$	No
Annual VCVT Scrapped Vehicles	VC, VT	vehicles	$= \sum_{SY} (\boldsymbol{Scrapped\ Vehicles})$	No
Annual VCVT Tailpipe Emissions	VC, VT	million metric tons	$= \sum_{FT} (\boldsymbol{VCVT\ Carbon\ Consumption\ Per\ Fuel})$	No
Annual VCVT Transportation Emissions	VC, VT	million metric tons	$= (\boldsymbol{Annual\ VCVT\ Tailpipe\ Emissions}) + (\boldsymbol{Annual\ VCVT\ Upstream\ Fuel\ Emissions})$	No
Annual VCVT Upstream Fuel Emissions	VC, VT	million metric tons	$= \frac{(\boldsymbol{Total\ VCVT\ VMT}) * (\boldsymbol{Upstream\ Emissions})}{\boldsymbol{1e12}}$	No
Annual VCVT VMT	VC, VT	miles	$= \sum_{SY} (\boldsymbol{Vehicle\ Stock\ VMT})$	No
Annual VCVT VP	VC, VT	vehicles	$= \sum_{SY} (\boldsymbol{Vehicle\ Stock\ Cohorts})$	No
Annual VMT Change EX	VC, VT, SY	miles	$= (\boldsymbol{Vehicle\ Cohort\ VMT}) * (\boldsymbol{Annual\ Growth\ in\ VMT})$	No
Annual VMT Change FC	VC, VT, SY	miles	$= (\boldsymbol{Vehicle\ Cohort\ VMT}) * (\boldsymbol{Change\ in\ VMT\ FC})$	No
Annual VT Grid Electricity Emissions	VT, FT	million metric tons	$= \sum_{VC} (\boldsymbol{Annual\ VCVT\ Grid\ Electricity\ Emissions})_{\boldsymbol{Electricity}}$	No
Annual VT Liquid Fuel Consumption	VT, FT	gallons	$= \sum_{VC} (\boldsymbol{Annual\ Liquid\ Fuel\ Consumption})$	No
Annual VT Scrapped Vehicles	VT	vehicles	$= \sum_{VC} (\boldsymbol{Annual\ VCVT\ Scrapped\ Vehicles})$	No
Annual VT Tailpipe Emissions	VT	million metric tons	$= \sum_{VC} (\boldsymbol{Annual\ VCVT\ Tailpipe\ Emissions})$	No
Annual VT Transportation Emissions	VT	million metric tons	$= \sum_{VC} (\boldsymbol{Annual\ VCVT\ Transportation\ Emissions})$	No
Annual VT Upstream Fuel Emissions	VT	million metric tons	$= \sum_{VC} (\boldsymbol{Annual\ VCVT\ Upstream\ Fuel\ Emissions})$	No

Variable *(alphabetical)*	Subscripts	Units	Equation	User Input ?
Annual VT VP	VT	vehicles	$=\sum_{VC}(\boldsymbol{Annual\ VCVT\ VP})$	No
At Generalized Cost	---	---	**User input constant**	Yes
At Market Share	---	---	**User input constant**	Yes
At Market Value	---	---	**User input constant**	Yes
Available Scrapped Vehicles	VC, VT	vehicles	**Dummy variable. Currently set to 0.**	No
B EXP Uk	VC	---	$=\boldsymbol{EXP}(\boldsymbol{B\ Uk})$	No
B LN SUM EXP	VC	---	$=\frac{\mathbf{1}}{(\boldsymbol{CE\ Vehicle\ Price})}*\ \boldsymbol{ln}(\boldsymbol{B\ SUM\ EXP})$	No
B SUM EXP	VC	---	$=\ \boldsymbol{VCVT\ EXP_{PHEV}}$	No
B Tech Type Share	VC	percent	$=\frac{\boldsymbol{B\ EXP\ Uk}}{\boldsymbol{SUM\ EXP\ Uk}}$	No
B Uk	VC	---	$=(\boldsymbol{VT\ Price\ Slope})*(\boldsymbol{B\ LN\ SUM\ EXP})$	No
B VCVT Shares	VC, VT	---	$=\frac{\boldsymbol{VCVT\ EXP}}{\boldsymbol{B\ SUM\ EXP}}$	No
Baseline Fuel Availability	VC, VT	fraction	**User input constants**	No
Baseline Fuel Economy	VC, VT	Miles per gallon	**User input constants**	Yes
Baseline Grid Electricity Price	FT	\$/kWh	**User input constant**	No
Baseline Liquid Fuel Price	FT	\$/gallon	**User input constant**	No
Baseline Maintenance Cost	VC, VT	\$(2007)	**User input constants**	Yes
Baseline Make/Model Availability	VC, VT	models	**User input constants**	No
Baseline New Vehicle Retail Price	VC, VT	\$	**User input constant**	Yes
Baseline Range	VC, VT	miles	**User input constants**	Yes
Beta Normalized VMT Difference	VC, VT, SY	---	$=[(-\boldsymbol{Scrappage\ Beta})*(\boldsymbol{Normalized\ VMT\ Difference})]$	No
C EXP Uk	VC	---	$=\boldsymbol{EXP}(\boldsymbol{C\ Uk})$	No
C LN SUM EXP	VC	---	$=\frac{\mathbf{1}}{(\boldsymbol{CE\ Vehicle\ Price})}*\ \boldsymbol{ln}(\boldsymbol{C\ SUM\ EXP})$	No
C SUM EXP	VC	---	$=\ \boldsymbol{VCVT\ EXP_{CGV}}+\ \boldsymbol{VCVT\ EXP_{HEV}}+\ \boldsymbol{VCVT\ EXP_{Diesel}}+\ \boldsymbol{VCVT\ EXP_{FFV}}$	No
C Tech Type Share	VC	percent	$=\frac{\boldsymbol{C\ EXP\ Uk}}{\boldsymbol{SUM\ EXP\ Uk}}$	No
C Uk	VC	---	$=(\boldsymbol{VT\ Price\ Slope})*(\boldsymbol{C\ LN\ SUM\ EXP})$	No
C VCVT Shares	VC, VT	---	$=\frac{\boldsymbol{VCVT\ EXP}}{\boldsymbol{C\ SUM\ EXP}}$	No

Variable *(alphabetical)*	Subscripts	Units	Equation	User Input ?
Carbon Fraction of Fuel	FT	ton/kilogram	**User Input Constants**	Yes
Carbon Per Gallon of Fuel	FT	ton/gallon	$= \frac{(\boldsymbol{Density\ of\ Fuel}) * (\boldsymbol{Carbon\ Fraction\ of\ Fuel})}{\mathbf{1000}}$	No
Carbon Per kWh	---	tons/kilowatt -hour	**User Input Constants**	Yes
Carbon Tax	FT	$/ton	**User input constant**	Yes
CE Acceleration	VC	---	**User input constant**	Yes
CE FE MCC 1	VC	---	**User input constants**	No
CE FE MCC 2	VC	---	**User input constants**	No
CE Fuel Availability 1	VC	---	**User input constant**	Yes
CE Fuel Availability 2	VC	---	**User input constant**	Yes
CE Fuel Cost	VC	---	**User input constant**	Yes
CE Home Refueling for EVs	VC	---	**User input constant**	Yes
CE Luggage Space	VC	---	**User input constant**	Yes
CE Maintenance Cost	VC	---	**User input constant**	Yes
CE Make/Model Availability	VC	---	**User input constant**	Yes
CE Multifuel Capability	VC	---	**User input constant**	Yes
CE Range	VC	---	**User input constant**	Yes
CE Top Speed	VC	---	**User input constant**	Yes
CE Vehicle Price	VC	---	**User input constant**	Yes
Change in FC Per Mile	VC, VT	percent	$= \frac{[(\boldsymbol{FC\ Per\ Mile})_{\boldsymbol{t}} - (\boldsymbol{FC\ Per\ Mile})_{\boldsymbol{t-1}}]}{(\boldsymbol{FC\ Per\ Mile})_{\boldsymbol{t-1}}}$	No
Change in Fuel Economy	VC, VT	percent	$= \frac{\boldsymbol{Fuel\ Economy}_{\boldsymbol{t}} - \boldsymbol{Fuel\ Economy}_{\boldsymbol{t-1}}}{\boldsymbol{Fuel\ Economy}_{\boldsymbol{t-1}}}$	No
Change in Grid Electricity Price	FT	percent	**User input constant**	Yes
Change in Liquid Fuel Price	FT	percent	**User input constants**	Yes
Change in Vehicle Price EX	VC, VT	percent	**User input constants**	Yes
Change in Vehicle Price FE	VC, VT	$	$= [(\boldsymbol{CE\ FE\ MCC\ 1}) * (\boldsymbol{Change\ in\ Fuel\ Economy})] + [(\boldsymbol{CE\ FE\ MCC\ 2}) * (\boldsymbol{Change\ in\ Fuel\ Economy})^{\mathbf{2}}]$	No
Change in VMT FC	VC, VT	miles	$= (\boldsymbol{Change\ in\ FC\ Per\ Mile}) * (\boldsymbol{Elsticity\ of\ VMT\ FV\ Per\ Mile})$	No

Variable *(alphabetical)*	Subscripts	Units	Equation	User Input ?
Consumer Utility	VC, VT	---	$= \sum_{VC/VT} (\boldsymbol{Vehicle\ Attribute\ Coefficients}) * (\boldsymbol{Vehicle\ Attributes})$	No
Consumer Utility of Fuels	VC, VT, FT	---	$= \sum_{VC/VT} (\boldsymbol{Fuel\ Attribute\ Coefficients}) * (\boldsymbol{Fuel\ Attributes})$	No
Conversion of C to CO2	---	---	**User Input Constants**	Yes
Density of Fuel	FT	kilogram/ gallon	**User Input Constants**	Yes
E Sum Weighted Mean	VC, VT	mpkWh	$= \sum_{SY} (\boldsymbol{E\ Weighted\ Mean\ Conversion})$	No
E Weighted Mean Conversion	VC, VT, SY	mpkWh	$= (\boldsymbol{Vehicle\ Stock\ Cohorts}) * (\boldsymbol{PHEV\ Electric\ Fuel\ Economy})$	No
E Weighted Mean mpkWh	VC, VT	mpkWh	$= \frac{(\boldsymbol{E\ SUM\ Weighted\ Mean})}{(\boldsymbol{Annual\ VCVT\ VP})}$	No
Elasticity of Vehicle Tech	---	---	**User input constant**	Yes
Elasticity of VMT FC Per Mile	VC, VT	---	**User input constant**	Yes
EPA Degradation Factor	VC, VT	percent	**Lookup Tables**	Yes
EXP Consumer Utility of Fuels	VC, VT, FT	---	$= \boldsymbol{EXP}(\boldsymbol{Consumer\ Utility\ of\ Fuels})$	No
EXP Normalized VMT Difference	VC, VT, SY	---	$= \boldsymbol{EXP}(\boldsymbol{Beta\ Normalized\ VMT\ Difference})$	No
F Fuel Availability	VC, VT	---	$= (\boldsymbol{P\ Fuel\ Availability}) * \frac{\boldsymbol{Fuel\ Choice\ Price\ Slope}}{\boldsymbol{CE\ Fuel\ Cost}}$	No
F Fuel Cost	VC, VT	---	$= (\boldsymbol{Fuel\ Choice\ Price\ Slope}) * (\boldsymbol{Relative\ Fuel\ Cost})$	No
F Range	VC, VT	---	$= (\boldsymbol{P\ Range}) * \frac{\boldsymbol{Fuel\ Choice\ Price\ Slope}}{\boldsymbol{CE\ Fuel\ Cost}}$	No
FC Per Mile	VC, VT	$/mile	$= \frac{(\boldsymbol{Taxed\ Fuel\ Price} * \boldsymbol{100})}{(\boldsymbol{LF\ Weighted\ Mean\ MPG})_{\boldsymbol{t}}}$	No
Fuel Availability	VC, VT	---	$= (\boldsymbol{Fuel\ Availability}_{\boldsymbol{t-1}}) + (\boldsymbol{Annual\ Change\ in\ Fuel\ Availability})$	No
Fuel Availability Growth	VC, VT	percent	**User input constants**	Yes
Fuel Choice Attribute Value	VC, VT	---	$= \frac{\boldsymbol{1}}{(\boldsymbol{Fuel\ Choice\ Price\ Slope})} * \boldsymbol{ln}(\boldsymbol{SUM\ EXP\ Consumer\ Utility\ of\ Fuels})$	No
Fuel Choice Elasticity	---	---	**User input constant**	Yes
Fuel Choice Price Slope	---	---	$= \frac{(\boldsymbol{Fuel\ Choice\ Elasticity})}{(\boldsymbol{Taxed\ Fuel\ Price}) * (\boldsymbol{1} - \boldsymbol{At\ Market\ Value})}$	No
Fuel Cost	VC, VT	$ / mile	$= \frac{(\boldsymbol{100} * \boldsymbol{Fuel\ Cost\ Per\ GGE})}{(\boldsymbol{Relative\ MPG}) * (\boldsymbol{Fuel\ Economy})}$	No
Fuel Cost Per GGE	FT	$/BTU GGE	$= \frac{(\boldsymbol{Taxed\ Fuel\ Price})}{(\boldsymbol{Fuel\ Energy\ Content}) * \boldsymbol{115000}}$	No

Variable *(alphabetical)*	Subscripts	Units	Equation	User Input ?
Fuel Economy	VC, VT	miles per gallon	$= \sum_{t} [(\boldsymbol{Fuel\ Economy})_{t-1} + (\boldsymbol{Annual\ Change\ in\ Fuel\ Economy})_{t}]$	No
Fuel Economy Growth CAFÉ	VT	percent	**User input constant**	Yes
Fuel Economy Growth EX	VC, VT	percent	**User input constants**	Yes
Fuel Energy Content	FT	BTU/gallon	**User input constants**	Yes
Fuel Tax	FT	\$/gallon	$= (\boldsymbol{Carbon\ Per\ Gallon\ of\ Fuel}) * (\boldsymbol{Carbon\ Tax})$	No
Historical VCVT Fuel Economy	VC, VT	miles per gallon	**Lookup Table**	No
Home Refueling for EVs	VC, VT	---	**User input constant**	Yes
Initial Model Year Accumulated VMT	VC, VT, SY	Miles	$= \sum_{SY=0}^{SY} (\boldsymbol{Initial\ Model\ Year\ VMT})$ **Note: The variable sums up each VC/VT cohort through the current vintage. For example, cohort 5 equals the sum of initial VMT from new through 5.**	No
Initial Model Year VMT	VC, VT, SY	miles	**Constant values**	Yes
Initial Vehicle Population Inputs	VC, VT, SY	vehicles	**Constant values**	Yes
Initial Vehicle Population Switch	VC, VT, SY	vehicles	**VCVT Switch dependent IF statements**	No
kg of Fuel Per Year	VC, VT, FT	kilogram	$= (\boldsymbol{Annual\ Liquid\ Fuel\ Consumption}) * (\boldsymbol{Density\ of\ Fuel})$	No
LF SUM Weighted Mean	VC, VT	miles per gallon	$= \sum_{SY} (\boldsymbol{LF\ Weighted\ Mean\ Conversion})$	No
LF Weighted Mean Conversion	VC, VT, SY	miles per gallon	$= (\boldsymbol{Vehicle\ Stock\ Cohorts}) * (\boldsymbol{Vehicle\ Stock\ Fuel\ Economy})$	No
LF Weighted Mean MPG	VC, VT	miles per gallon	$= \frac{(\boldsymbol{LF\ SUM\ Weighted\ Mean})}{(\boldsymbol{Annual\ VCVT\ VP})}$	No
Luggage Space	VC, VT	cubic feet	**User input constants**	Yes
Maintenance Cost	VC, VT	\$(2007)	$= \sum_{t} [(\boldsymbol{Maintenance\ Cost})_{t-1} + (\boldsymbol{Annual\ Change\ in\ Maintenance\ Cost})_{t}]$	No
Maintenance Cost Growth	VC, VT	percent	**User input constants**	Yes
Make/Model Availability	VC, VT	---	$= (\boldsymbol{Make - Model\ Availability}_{t-1}) + (\boldsymbol{Annual\ Change\ in\ Make - Model\ Availability})$	No
Make/Model Availability Growth	VC, VT	percent	**User input constants**	Yes
Median Accumulated VMT	VC	miles	**User input constants**	Yes
Multifuel Capability	VC, VT	---	**User input constants**	Yes

Variable *(alphabetical)*	Subscripts	Units	Equation	User Input ?
Normalized VMT Difference	VC, VT, SY	---	$= \frac{[(\boldsymbol{Vehicle\ Cohort\ Accumulated\ VMT}) - (\boldsymbol{Median\ Accumulated\ VMT})]}{(\boldsymbol{VMT\ Normalization\ Constant})}$ **Where, *Initial Model Year Accumulated VMT* data is used if *Scrappage-VMT Feedback Switch* is set to 1. This allows the feedback effects to be turned 'off' and use baseline values for scrappage rates.**	No
Old FC Per Mile	VC, VT	$/mile	$= \frac{(\boldsymbol{Taxed\ Fuel\ Price} * \boldsymbol{100})}{(\boldsymbol{LF\ Weighted\ Mean\ MPG})_{\boldsymbol{t-1}}}$	No
Old Fuel Economy	VC, VT	miles per gallon	$= \boldsymbol{Fuel\ Economy}_{\boldsymbol{t-1}}$	No
Old Vehicle Cohort Accumulated VMT	VC, VT, SY	miles	$= \sum_{\boldsymbol{t=0}}^{\boldsymbol{SY}} (\boldsymbol{Vehicle\ Cohort\ VMT})_{\boldsymbol{t-1}}$ **Where, *Initial Model Year Accumulated VMT* is used as an initial condition.** **Note: Variable sums each VC/VT cohort to represent the accumulation of miles per vehicle as each vehicle ages in the model. The variable is delayed one time step to represent the accumulation from the previous year.**	No
P Acceleration	VC, VT	---	$= (\boldsymbol{CE\ Acceleration}) * (\boldsymbol{Acceleration})$	No
P Fuel Availability	VC, VT	---	$= (\boldsymbol{CE\ Fuel\ Availability\ 1}) * [\boldsymbol{EXP}((\boldsymbol{CE\ Fuel\ Availability\ 2}) * (\boldsymbol{Acceleration}))]$	No
P Fuel Cost	VC, VT	---	$= (\boldsymbol{CE\ Fuel\ Cost}) * (\boldsymbol{Fuel\ Cost})$	No
P Home Refueling for EVs	VC, VT	---	$= (\boldsymbol{CE\ Home\ Refueling\ for\ EVs}) * (\boldsymbol{Home\ Refueling\ for\ EVs})$	No
P Luggage Space	VC, VT	---	$= (\boldsymbol{CE\ Luggage\ Space}) * \frac{\boldsymbol{Luggage\ Space}_{\boldsymbol{CGV}}}{(\boldsymbol{Luggage\ Space}_{\boldsymbol{VC/VT}})}$	No
P Maintenance Cost	VC, VT	---	$= (\boldsymbol{CE\ Maintenance\ Cost}) * (\boldsymbol{Maintenance\ Cost})$	No
P Make/Model Availability	VC, VT	---	$= (\boldsymbol{CE\ Make - Model\ Availability}) * \boldsymbol{ln} \frac{\boldsymbol{Make - Model\ Availability}_{\boldsymbol{VC/VT}}}{\boldsymbol{Make - Model\ Availability}_{\boldsymbol{CGV}}}$	No
P Multifuel Capability	VC, VT	---	$= (\boldsymbol{CE\ Multifuel\ Capability}) * (\boldsymbol{Multifuel\ Capability})$	No
P Range	VC, VT	---	$= (\boldsymbol{CE\ Range}) * \frac{\boldsymbol{1}}{(\boldsymbol{Range})}$	No
P Top Speed	VC, VT	---	$= (\boldsymbol{CE\ Top\ Speed}) * (\boldsymbol{Top\ Speed})$	No
P Vehicle Price	VC, VT	---	$= (\boldsymbol{CE\ Vehicle\ Price}) * (\boldsymbol{Vehicle\ Price})$	No
PHEV Electric Fuel Economy	VC	mpkWh	**User input constant**	Yes
Probability of Fuel Choice	VC, VT, FT	percent	$= \frac{(\boldsymbol{EXP\ Consumer\ Utility\ of\ Fuels})}{(\boldsymbol{SUM\ EXP\ Consumer\ Utility\ of\ Fuels})}$	No
Purchases by VC	VC	vehicles	$= (\boldsymbol{Total\ New\ Sales}) * (\boldsymbol{VC\ Shares})$	No
Range	VC, VT	miles	$= \sum_{\boldsymbol{t}} [(\boldsymbol{Range})_{\boldsymbol{t-1}} + (\boldsymbol{Annual\ Change\ in\ Range})_{\boldsymbol{t}}]$	No
Range Growth	VC, VT	percent	**User input constants**	Yes
Rebound Effect Switch	---	---	**User input constant. Set = 0 for 'off'; set = 1 for 'on'.**	Yes
Relative Fuel Cost	VC, VT, FT	$/mile	$= \frac{(\boldsymbol{100} * \boldsymbol{Fuel\ Cost\ Per\ GGE})}{(\boldsymbol{Fuel\ Economy}) * (\boldsymbol{Relative\ MPG})}$	No
Relative MPG	VC,VT	---	**User input constants**	Yes
Scrappage Alpha	VC, VT	---	**User input constant**	No

Variable *(alphabetical)*	Subscripts	Units	Equation	User Input ?
Scrappage Beta	VC	---	**User input constant**	Yes
Scrappage Rate	VC, VT, SY	percent	$= \frac{\mathbf{1}}{[(\boldsymbol{Scrappage\ Alpha}) + (\boldsymbol{EXP\ Normalized\ VMT\ Difference})]}$ $\boldsymbol{where\ Scrappage\ Rate} = \mathbf{0}\ \boldsymbol{when\ SY} \leq \mathbf{5}$	No
Scrappage-VMT Feedback Switch	---	---	**User input constant. Set = 0 for 'off'; set = 1 for 'on'.**	Yes
Scrapped Vehicles	VC, VT, SY	vehicles	$= (\boldsymbol{Vehicle\ Stock\ Cohorts}) * (\boldsymbol{Scrappage\ Rate})$	No
Scrapped Vehicles Stock	VC, VT, SY	vehicles	$= \sum_{\boldsymbol{SY}} [(\boldsymbol{Scrapped\ Vehicles})] - (\boldsymbol{Available\ Scrapped\ Vehicles})$	No
Stock Conversion	SY	---	**= 0,1,2,…20.**	No
SUM EXP Consumer Utility of Fuels	VC, VT	---	$= (\boldsymbol{EXP\ Consumer\ Utility\ of\ Fuels})_{\boldsymbol{Gasoline}} + (\boldsymbol{EXP\ Consumer\ Utility\ of\ Fuels})_{\boldsymbol{E85}}$	No
SUM EXP Uk	VC	---	$= (\boldsymbol{C\ EXP\ Uk}) + (\boldsymbol{B\ EXP\ Uk})$	No
Taxed Fuel Price	FT	$/gallon	$= (\boldsymbol{Untaxed\ Fuel\ Price}) + (\boldsymbol{Fuel\ Tax})$	No
Taxed Vehicle Price	VC, VT	$ (2007)	$= (\boldsymbol{Untaxed\ Fuel\ Economy}) - (\boldsymbol{Vehicle\ Subsidies})$	No
Top Speed	VC, VT	miles per hour	**User input constants**	Yes
Total LDV Emissions	---	million metric tons	$= \sum_{\boldsymbol{t}} [(\boldsymbol{Total\ LDV\ Emissions})_{\boldsymbol{t-1}} + (\boldsymbol{Annual\ LDV\ Emissions})_{\boldsymbol{t}}]$	No
Total New Sales	---	vehicles	$= [(\boldsymbol{Annual\ Change\ in\ Sales}) * (\boldsymbol{Annual\ Scrapped\ Vehicles})] + \boldsymbol{Annual\ Scrapped\ Vehicles}$	No
Total VC Scrapped Vehicles	VC	vehicles	$= \sum_{\boldsymbol{VT}} (\boldsymbol{Total\ VT\ Scrapped\ Vehicles})$	No
Total VC VMT	VC	miles	$= \sum_{\boldsymbol{VT}} (\boldsymbol{Total\ VCVT\ VMT})$	No
Total VC VP	VC	vehicles	$= \sum_{\boldsymbol{t}} [(\boldsymbol{Total\ VCVT\ VP})_{\boldsymbol{t-1}} + (\boldsymbol{Annual\ VCVT\ VP})_{\boldsymbol{t}}]$	No
Total VCVT Grid Electricity Consumption	VC, VT, FT	kWh	$= \sum_{\boldsymbol{t}} [(\boldsymbol{Total\ VCVT\ Grid\ Electricity\ Consumption})_{\boldsymbol{t-1}} + (\boldsymbol{Annual\ VCVT\ Grid\ Electricity\ Consumption})_{\boldsymbol{t}}]$	No
Total VCVT Grid Electricity Emissions	VC, VT, FT	million metric tons	$= \sum_{\boldsymbol{t}} [(\boldsymbol{Total\ VCVT\ Grid\ Electricity\ Emissions})_{\boldsymbol{t-1}} + (\boldsymbol{Annual\ VCVT\ Grid\ Electricity\ Emissions})_{\boldsymbol{t}}]$	No
Total VCVT Liquid Fuel Consumption	VC, VT, FT	gallons	$= \sum_{\boldsymbol{t}} [(\boldsymbol{Total\ VCVT\ Liquid\ Fuel\ Consumption})_{\boldsymbol{t-1}} + (\boldsymbol{Annual\ Liquid\ Fuel\ Consumption})_{\boldsymbol{t}}]$	No
Total VCVT Tailpipe Emissions	VC, VT	million metric tons	$= \sum_{\boldsymbol{t}} [(\boldsymbol{Total\ VCVT\ Tailpipe\ Emissions})_{\boldsymbol{t-1}} + (\boldsymbol{Annual\ VCVT\ Tailpipe\ Emissions}_{\boldsymbol{t}}]$	No
Total VCVT Transportation Emissions	VC, VT	million metric tons	$= \sum_{\boldsymbol{t}} [(\boldsymbol{Total\ VCVT\ Transportation\ Emissions})_{\boldsymbol{t-1}} + (\boldsymbol{Annual\ VCVT\ Transportation\ Emissions})_{\boldsymbol{t}}]$	No
Total VCVT Upstream Fuel Emissions	VC, VT	million metric tons	$= \sum_{\boldsymbol{t}} [(\boldsymbol{Total\ VCVT\ Upstream\ Fuel\ Emissions})_{\boldsymbol{t-1}} + (\boldsymbol{Annual\ VCVT\ Uptream\ Fuel\ Emissions})_{\boldsymbol{t}}]$	No

Variable *(alphabetical)*	Subscripts	Units	Equation	User Input ?
Total VCVT VMT	VC, VT	miles	$= \sum_{SY} (\boldsymbol{Stock\ VT\ VMT})$	No
Total VCVT VP	VC, VT	vehicles	$= \sum_{t} [(\boldsymbol{Total\ VC\ VP})_{t-1} + (\boldsymbol{Annual\ VC\ VP})_{t}]$	No
Total VMT	VC, VT	miles	$= \sum_{t} [(\boldsymbol{Total\ VMT})_{t-1} + (\boldsymbol{Annual\ VCVT\ VMT})_{t}]$	No
Total VT Scrapped Vehicles	VC, VT	vehicles	$= \sum_{SY} (\boldsymbol{Scrapped\ Vehicles\ Stock})$	No
Total VT VMT	VT	miles	$= \sum_{VC} (\boldsymbol{Total\ VCVT\ VMT})$	No
Total VT VP	VT	vehicles	$= \sum_{t} [(\boldsymbol{Total\ VT\ VP})_{t-1} + (\boldsymbol{Annual\ VT\ VP})_{t}]$	No
Untaxed Fuel Price	FT	$/gallon	$= \sum_{t} [(\boldsymbol{Untaxed\ Fuel\ Price})_{t-1} + (\boldsymbol{Annual\ Change\ in\ Untaxed\ Fuel\ Price})_{t}]$ **Where, variable calculates both liquid fuel prices and electricity prices.**	No
Untaxed Vehicle Price	VC, VT	$ (2007)	$= \sum_{t} [(\boldsymbol{Vehicle\ Price})_{t-1} + (\boldsymbol{Annual\ Change\ in\ Vehicle\ Price})_{t}]$	No
Upstream Emissions Factor	VC, VT	ton/gallon	$= (\boldsymbol{Upstream\ Feedstock\ Emissions\ Factor}) + (\boldsymbol{Upstream\ Fuel\ Emissions\ Factor})$	No
Upstream Feedstock Emissions Factor	VC,VT	ton/gallon	**User input constants**	Yes
Upstream Fuel Emissions Factor	VC, VT	ton/gallon	**User input constants**	Yes
VC New Consumer Vehicle Purchases	VC	vehicles	$= \sum_{VT} (\boldsymbol{New\ Consumer\ Vehicle\ Purchases})$	No
VC Shares	VC	percent	**User input constants**	Yes
VCVT Carbon Consumption Per Fuel	VC, VT, FT	million metric tons	$= \frac{(\boldsymbol{kg\ of\ Fuel\ Per\ Year}) * (\boldsymbol{Carbon\ Fraction\ of\ Fuel}) * (\boldsymbol{Conversion\ of\ C\ t}}{\boldsymbol{1e9}}$	No
VCVT EXP	VC, VT	---	$= \boldsymbol{EXP}(\boldsymbol{Consumer\ Utility})$	No
VCVT Grid Electricity Consumption	VC, VT, FT	kWh	$= \sum_{SY} (\boldsymbol{Vehicle\ Stock\ Grid\ Electricity\ Consumption})_{\boldsymbol{Electricity}}$	No
VCVT Liquid Fuel Consumption	VC, VT, FT	gallons	$= \sum_{VT} (\boldsymbol{Annual\ Liquid\ Fuel\ Consumption})$	No
VCVT New Consumer Vehicle Purchases	VC, VT	vehicles	$= (\boldsymbol{Purchases\ by\ VC}) * (\boldsymbol{VT\ PofP})$	No
VCVT Switch	VC, VT	---	**User input constants**	Yes

Variable *(alphabetical)*	Subscripts	Units	Equation	User Input ?
Vehicle Cohort Accumulated VMT	VC, VT, SY	miles	$= \sum_{t=0}^{SY} [(\boldsymbol{Old\ Vehicle\ Cohort\ Accumulated\ VMT})_{t-1} + (\boldsymbol{Vehicle\ Cohort\ VMT})_t]$ **Where, *Initial Model Year Accumulated VMT* is used as an initial condition.** **Note: Variable sums the current time steps VC/VT cohort VMT with the previous year's accumulation to represent the accumulation of miles per vehicle as each vehicle ages in the model.**	No
Vehicle Cohort VMT	VC, VT, SY	miles	$= \sum_{t} [(\boldsymbol{Vehicle\ Cohort\ VMT})_{t-1} + (\boldsymbol{Annual\ Change\ in\ VMT})_t]$	No
Vehicle Purchases	VC, VT	vehicles	$= (\boldsymbol{New\ Consumer\ Vehicle\ Purchases})$	No
Vehicle Stock Cohorts	VC, VT, SY	vehicles	$= (\boldsymbol{Vehicle\ Purchases}) - (\boldsymbol{Aging\ Vehicles}) - (\boldsymbol{Scrapped\ Vehicles})$	No
Vehicle Stock Fuel Economy	VC, VT, SY	---	**Time dependent IF statements**	No
Vehicle Stock Grid Electricity Consumption	VC, VT, SY, FT	kWh	$= \frac{\boldsymbol{Vehicle\ Stock\ VMT\ Per\ Fuel}}{\boldsymbol{PHEV\ Electric\ Fuel\ Economy}}$	No
Vehicle Stock Liquid Fuel Consumption	VC, VT, SY, FT	gallons	**Fuel Type dependent IF statements**	No
Vehicle Stock VMT	VC, VT, SY	miles	$= (\boldsymbol{Vehicle\ Stock\ Cohorts}) * (\boldsymbol{Vehicle\ Cohort\ VMT})$	No
Vehicle Stock VMT Per Fuel	VC, VT, SY, FT	miles	**Fuel Type dependent IF statements**	No
Vehicle Subsidies	VT	$	**User input constants**	Yes
VMT Normalization Constant	VC	miles	**User input constants**	Yes
VT New Consumer Vehicle Purchases	VT	vehicles	$= \sum_{VC} (\boldsymbol{New\ Consumer\ Vehicle\ Purchases})$	No
VT PofP	VC, VT	percent	$= (\boldsymbol{C\ VT\ Shares}) * (\boldsymbol{C\ Tech\ Type\ Share})$	No
VT Price Slope	---	---	$= \frac{(\boldsymbol{Elasticity\ of\ Vehicle\ Tech})}{(\boldsymbol{At\ Generalized\ Cost}) * (\boldsymbol{1 - At\ Market\ Share})}$	No
VT Sales Market Share	VT	percent	$= \frac{(\boldsymbol{VT\ New\ Consumer\ Vehicle\ Purchases_{VT}})}{\sum_{VT}(\boldsymbol{VT\ New\ Consumer\ Vehicle\ Purchases})}$	No
Year Conversion	---	---	**Lookup Table**	No
Year Fuel Economy Standard Met	---	year	**User input constant**	Yes
Year Subsidies End	---	year	**User input constant**	Yes

Appendix 3 CLIMATS Quantitative Model Validation

Before constructing policy scenarios, CLIMATS is validated by comparing it to similar data predictions found in the Energy Information Administration (EIA) Annual Energy Outlook (AEO) 2009 Update. The EIA attempts to simulate fuel consumption and emissions production of the entire US energy system, including the transportation sector. A short description on EIA's simulation National Energy Model was presented earlier.

A comparison between the two models comes with a series of caveats. First, as stated previously, the use of CLIMATS is not an attempt to simulate the future transportation sector, but instead meant to test the impact of policies. Even so, steps have been taken to use a more realistic representation of LDV dynamics. For instance, feedbacks were meticulously justified when included in the CLD and an extensive literature search was completed to quantify many of them. Differences such as not including all vehicle classes and types do alter modeling results, though.

Second, EIA's model endogenously calculates many variables currently exogenous in CLIMATS. Fuel price, macroeconomic dynamics, vehicle class share, and the inception of new vehicle technologies in the market are calculated internally (EIA, 2007c). Therefore, a direct comparison is not possible, but instead *trends* are tested to ensure that the CLIMATS model is producing an accurate magnitude of change over time.

Third, the AEO 2009 Update takes into account the 2007-2009 economic recession. Through macroeconomic dynamics, the recession results in drastic short term changes in vehicle sales that affect other variables. CLIMATS does not include a macroeconomic model, so recessionary effects are not reflected in data output.

Appendix 5.3 lists all values used for the model validation scenario. AEO 2009 Update data is manipulated to produce average annual growth rate values for user input variables like fuel price, fuel economy, range, vehicle price, new vehicle sales, and miles traveled. Market penetration for alternative fuel vehicles is exogenously set in CLIMATS based on AEO results. This generalization assumes AEOs vehicle technology and producer submodel is correct because CLIMATS doesn't internally decide when new technologies will enter the market.

For the purposes of validation, two comparisons are made. First, CLIMATS is run using AEO data with both the rebound effect and VMT-Scrappage feedbacks turned off. Here, only exogenous growth rates are used to drive future model changes. Second, CLIMATS is run using AEO data with both feedbacks turned on (with a 10% rebound effect). The purpose of this method is to compare the impact of the feedbacks in relation to AEO output and to see the difference in results. The impact of these feedbacks on policy portfolio effectiveness is one determining factor used in this thesis.

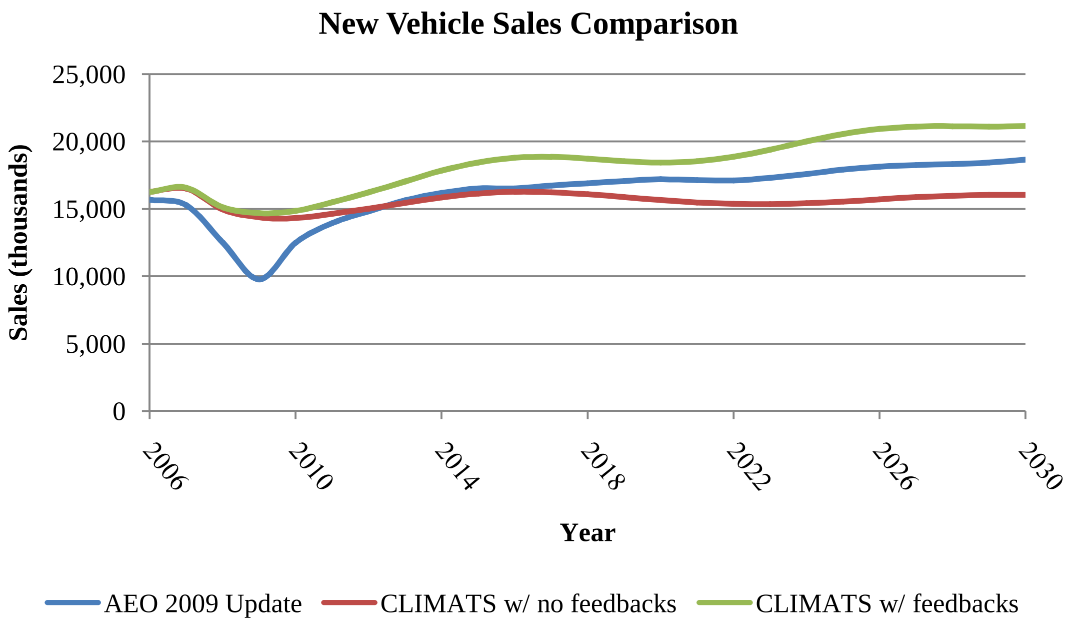

Figure 63 Comparison of CLIMATS and AEO 2009 Update new vehicle sales data.

Figure 63 compares total new vehicle sales (all classes and types). Ignoring the recession driven drop in AEO total sales from 2007-2010, CLIMATS produces a reasonably close fit. Data differences trend towards under representing sales with feedbacks turned off (range of -11% to 2.3%) and over representing sales with feedbacks turned on (range of 10% to 20%). The feedback effects are important to note here because the additional sales are driven by consumers increasing their scrappage rates due to traveling more. This increase scrappage drives greater new vehicle sales and it is a feedback not detailed in AEOs model description (EIA, 2007c).

Table 10 breaks down output differences by vehicle type. Here, the consumer choice submodel results are stark. The market share of alternative fuel vehicles is drastically different between CLIMATS and AEO, mainly because consumers choose diesel vehicles over HEVs, PHEVs, and FFVs. Reasons for this difference are attributed to AEO not publishing all vehicle characteristic data, resulting in the use of researcher defined average values to fill gaps. Also, AEO builds in the effects of currently implemented policies explicitly targeting HEVs, PHEVs, diesel, and FFVs that are not included in the CLIMATS scenarios. Tax breaks, subsidies, increased infrastructure, and other price signals are included and AEO assumes the result will be a more rapid penetration of these vehicles (EIA, 2007b).

	All Conventional Gasoline		All Diesel		All Hybrid Electric		All Plug in Hybrid		All Flex Fuel (E85)	
	Feedbacks	No Feedbacks	Feedbacks	No Feedbacks	Feedbacks	No Feedbacks	Feedbacks	No Feedbacks	Feedbacks	No Feedbacks
2006	7%	7%	796%	796%	71%	71%	0%	0%	115%	116%
2010	6%	2%	978%	939%	67%	61%	0%	0%	-36%	-38%
2015	8%	-6%	543%	460%	-21%	-32%	-100%	-100%	-42%	-50%
2020	13%	-4%	261%	208%	-55%	-62%	-99%	-99%	-36%	-46%
2025	25%	-5%	169%	103%	-67%	-75%	-96%	97%	-14%	-35%
2030	32%	0%	121%	67%	-74%	-80%	-86%	-89%	-5%	-21%

Table 10 Percent difference between CLIMATS validation case and AEO 2009 Update values for new vehicle sales by type.

Even though directly validating CLIMATS sales data at the vehicle type level is difficult, the trend in total sales and the effects of feedbacks are realistic and in line with EIA predictions.

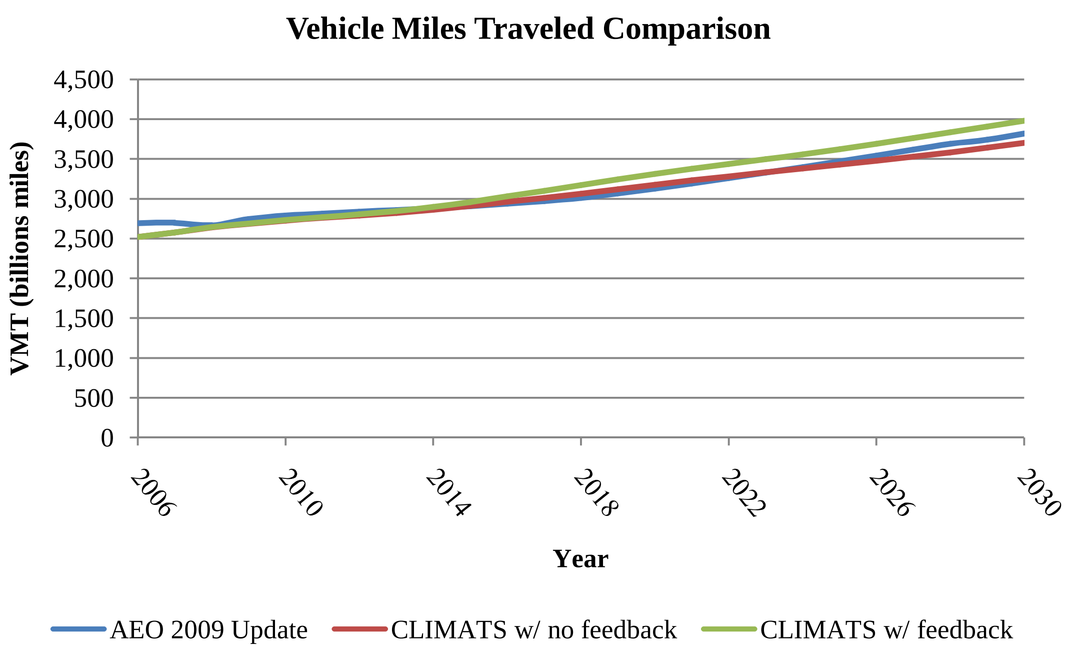

Figure 64 Comparison of CLIMATS and AEO 2009 Update VMT data.

The same can be said of VMT. The no feedback CLIMATS case compares very well with AEO data, resulting in only a 0% to 5% difference. The feedback case, where the rebound effect leads to increased travel as more fuel efficient vehicles enter the market due to a decrease in the cost of driving, results in an overall increase in VMT (difference of 2% to 10% from AEO).

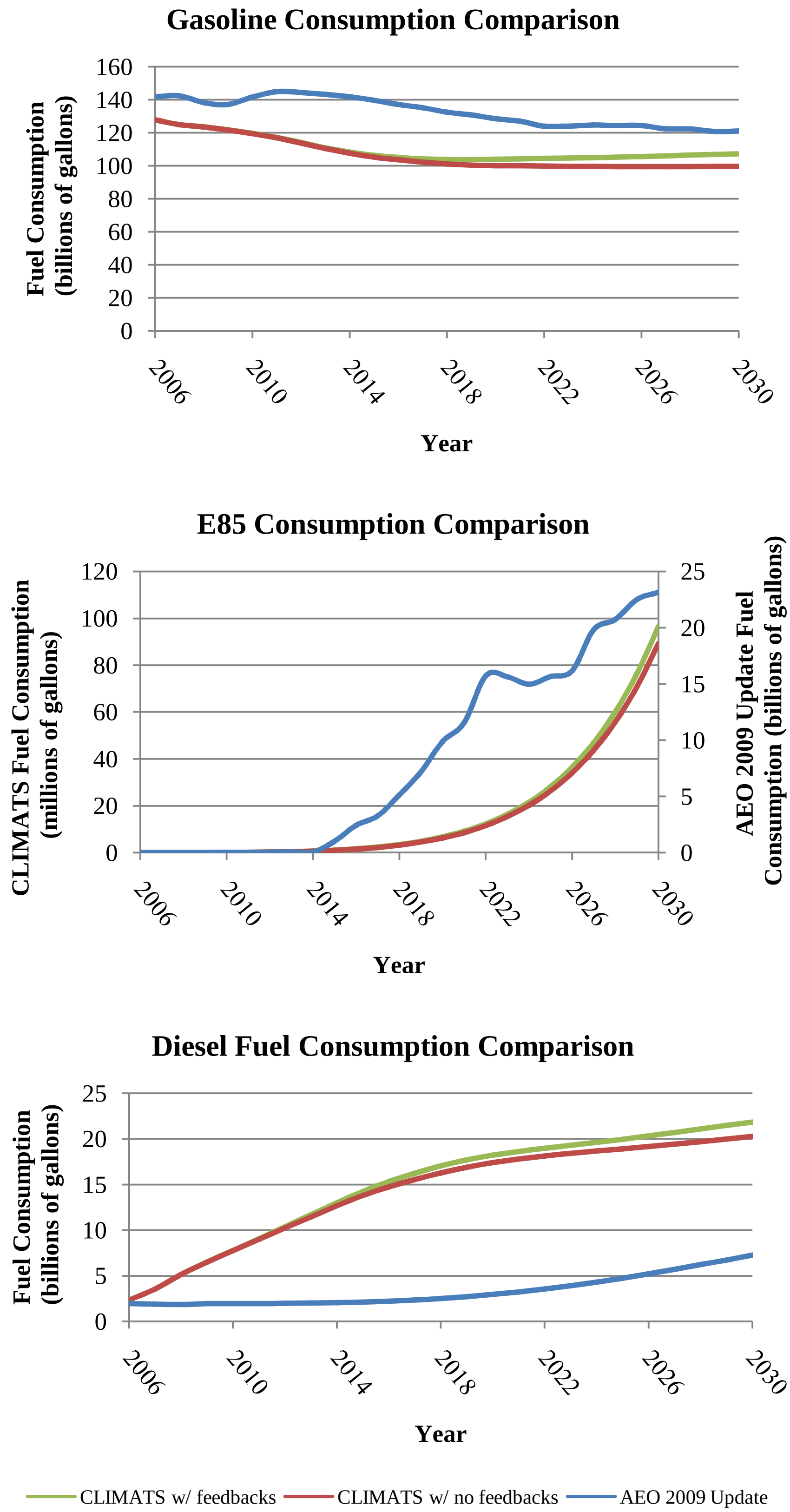

Figure 65 Comparison of CLIMATS and AEO 2009 Update fuel consumption data.

The same market share issue discussed above resulted in the same magnitude of error for VMT and fuel consumption data parsed by vehicle type. The graphs presented in Figure 65 illustrate a good comparison for gasoline consumption, but expectedly skewed differences among E85 and diesel. Grid electricity consumption is not shown due to AEO only publishing total consumption values and not those specific to PHEVs. Note that CLIMATS produces significantly less E85 consumption (10 times as less) than AEO, though both trend much the same.

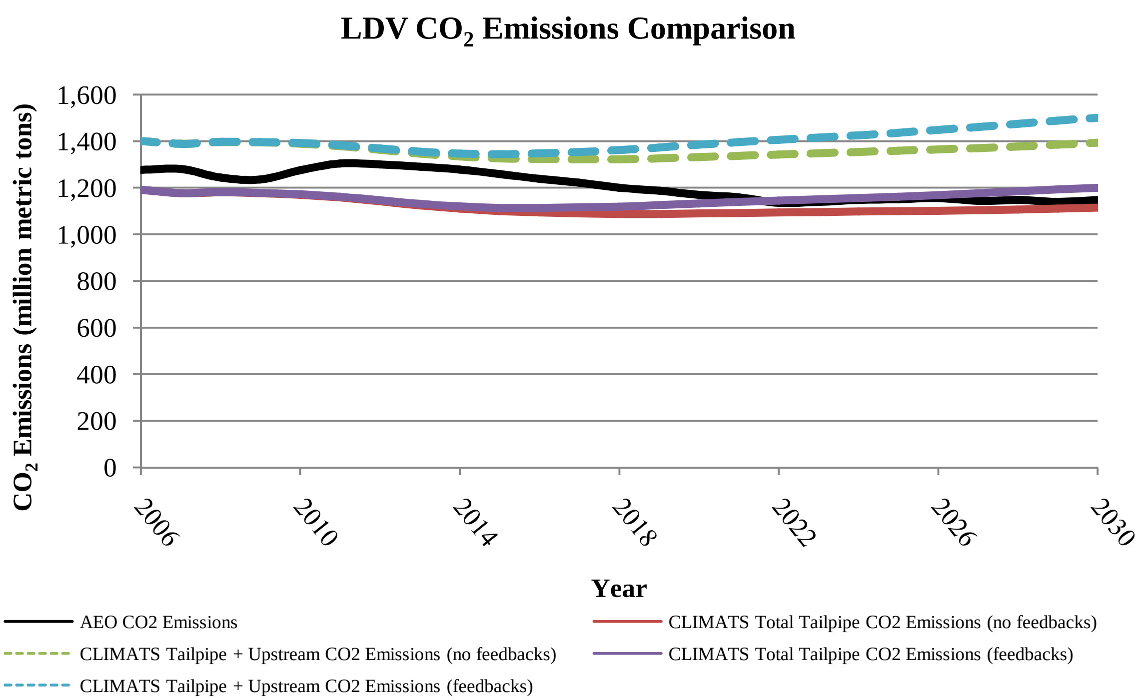

Figure 66 Comparison of CLIMATS and AEO 2009 Update CO_2 emissions data.

Lastly, validation of CO_2 emissions shows good agreement in magnitude as well as an important difference in the models. Figure 66 plots CLIMATS tailpipe emissions under both feedback scenarios, showing an excellent comparison, where the feedback case trends upward in the second half of the simulation as consumers of alternative fuel vehicles drive more. By adding upstream fuel emissions to the sum, the difference exceeds roughly 100 million metric tons of CO_2, or an increase of 10% to 15%. Such an amount is not trivial and including these emissions could drastically alter whether a policy reaches its intended consequences.

Generally, CLIMATS performed well using AEO scenario data, given the many structural differences. The additional feedbacks and emission sources compiled in the model provided pronounced differences in output that are important to consider. While not perfectly mimicking EIA predictions, CLIMATS produces usable, reasonably accurate data ready for policy analysis.

Appendix 4 CLIMATS Quantitative Model Sensitivity Analysis

Sensitivity analysis is a process that tests the degree of influence variables have on model results. This is useful in that it allows for an understanding of the different outcomes that can arise given varying magnitudes of perturbations to baseline assumptions (Haug et al., 1986; Winebrake and Creswick, 2003). In the case of CLIMATS, it will also provide an initial analysis of general policy impacts on key variables. Deaton and Winebrake (2000) provide a four step method for performing this analysis:

1. Identify exogenous variables in the model whose values do not depend on other quantities, but are instead set by the user.
2. For each exogenous variable, make a series of model runs, changing values over a certain range great enough to yield noticeable changes in results.
3. Observe and compare the system behavior and outcome for each run. Determine the extent to which the system behavior changes whenever each exogenous variable is changed. Changes in the system can be represented as either a difference in *level* (e.g. annual change in emissions) or *shape* (e.g. trend in emissions over time) of the response.
4. Identify the level of impact of each exogenous variable and provide a rationale for the classification.

This analysis is conducted in two parts. In both comparisons, the AEO 2009 Update CLIMATS simulation (with feedbacks) discussed in the model validation section is considered the base case. First, key exogenous variables related to fuel consumption and emissions are tested with experimental bounds of +/- 25%. A general understanding of each variable's leverage in the model (and the policy implications) regarding total emissions reduction is parsed out. Then, experimental bounds are increased and illustrated for variables commonly discussed in the literature (e.g. the price of gasoline) to provide a broader picture of its importance.

Second, vehicle attribute variables represented in the consumer choice submodel are tested with experimental bounds realistic for each variable. A general understanding of each variable's leverage in the model regarding vehicle type market share is parsed out. Then, experimental bounds are increased and illustrated for high impact variables to provide the extent of influence.

Leverage is discussed in the short term (2015) and long term (2030). This gauges whether a variable's leverage changes over time, an important characteristic to decision makers. Impact ratings are be ranked none, low, and high.

Low leverage variables are those that have a minimal impact on the model (Deaton and Winebrake, 2000). While not directly important to emissions reductions, low leverage variables may provide an option for policy makers that have other benefits (e.g. economic) or may be important in concert with changes to other system variables.

High leverage variables are those that have significant and often times dramatic impact on the model. Such variables are directly important to emissions reductions and may provide the best opportunity for policy makers to impact the system. Policies, individually and in combination, should be built around such variables to meet intended consequences.

Appendix 4.1 Fuel Consumption and Emissions Variables

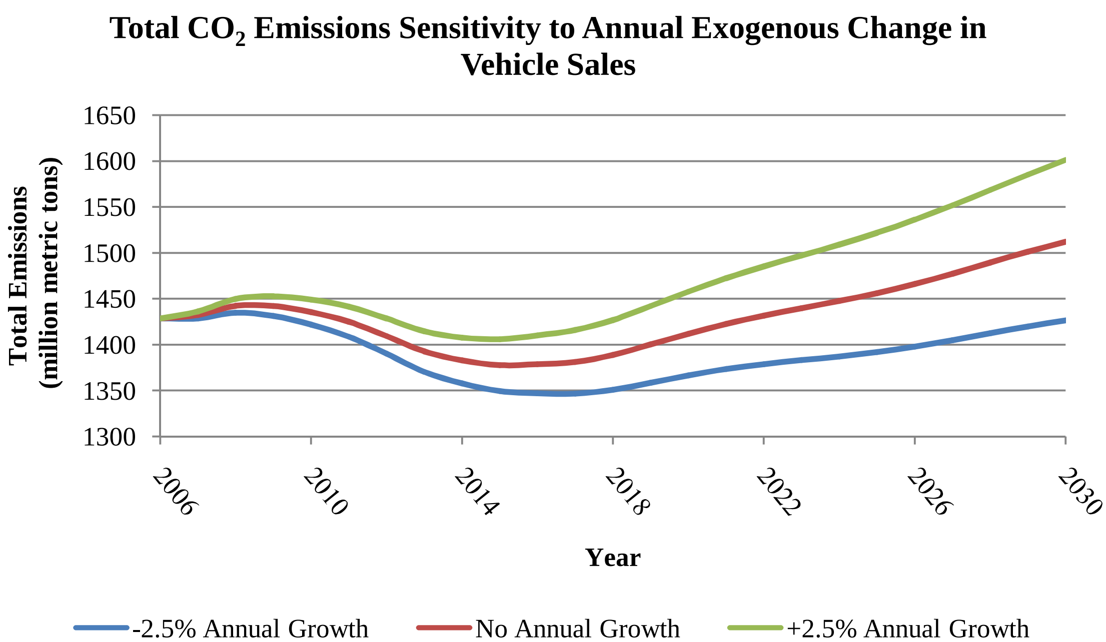

Figure 67 Sensitivity Analysis: Response of total CO_2 emissions to changes in annual vehicle sales.

Table 11 outlines variables related to fuel consumption and emissions not included in the consumer choice submodel. Only variables that represent dynamics that realistically change in the transportation system are included. Exogenous variables such as *Initial Vehicle Population* are not included because they are static quantities representing real world values. Of those in the table, three variables are discussed.

Annual Change in Vehicle Sales represent the annual addition of vehicles to the population aside from the number of vehicles replacing those that are scrapped (represented by *Annual Scrapped Vehicles*). This case has policy significance because experts and decision makers have discussed policies aimed at reducing driving behaviors, which could include owning less vehicles (2009; Frank and Pivo, 1994).

Figure 67 shows the emission results in response to a range of annual sales trends. According to the TEDB, total retail vehicle sales have averaged an annual change of less than 1% since 1970, so +/- 2.5% are considered reasonable bounds for analysis (Davis and Diegal, 2007). Of note is the increase in total emissions in the long term regardless of the scenario. Therefore, policies individually implemented to effect vehicle sales will be limited in reducing LDV emissions.

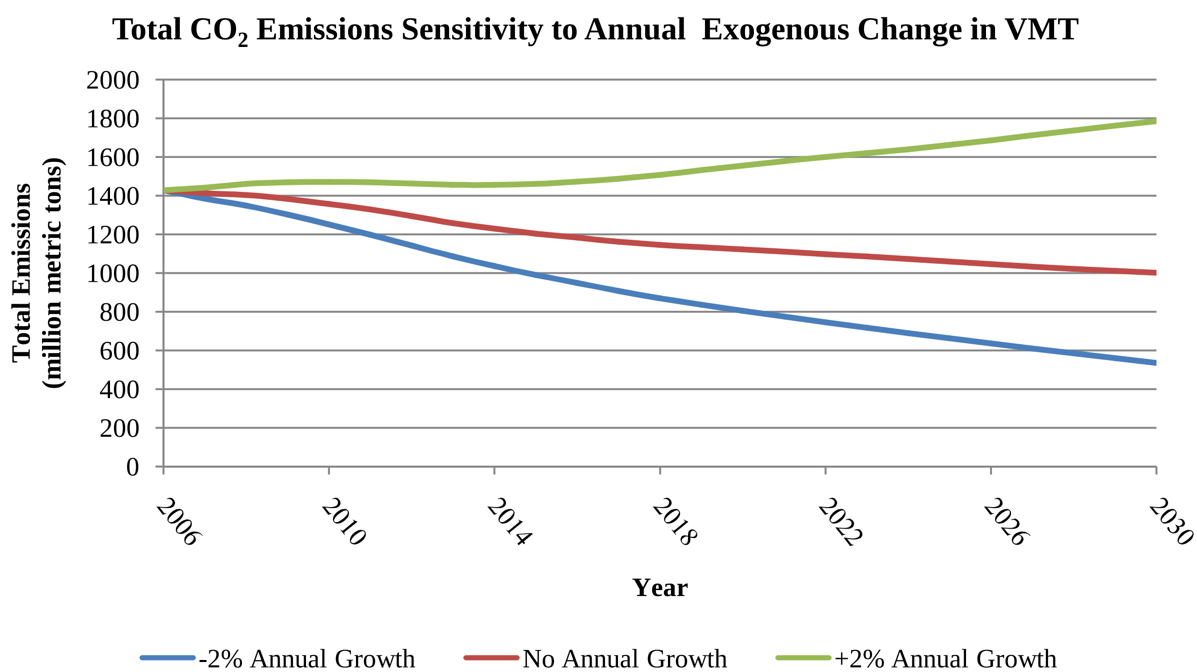

Figure 68 Sensitivity Analysis: Response of total CO_2 emissions to changes in annual VMT.

Table 11 Sensitivity analysis of key fuel and emissions variables.

Variable	Values		2015 Total Emissions Values	2015 % Difference	2030 Total Emissions Values	2030 % Difference	Rationale	Short Term Leverage	Long Term Leverage
Annual Change in Sales (percent)	25%	0.014125	1387	-0.22%	1542	-0.58%	*Annual Change in Sales* will not have a high impact on total emissions, within realistic bounds. Only a drastic increase in sales, on the order greater than +/-2%, will lead to a significant change in CO2. Such change can only be attributed to a cultural shift, such as consumers adding an additional vehicle to a household or a spike in the number of driving age consumers.	None	Low
	Baseline	0.0113	1390	---	1551	---			
	-25%	0.008475	1392	0.14%	1560	0.58%			
Annual Growth in VMT (percent)	25%	0.018625	1435	3.24%	1699	9.54%	*Annual Growth in VMT* will have a high impact on total emissions due to it being a key component of tailpipe emissions. Policies aimed at effecting riving habits are important to consider, though difficult to implement.	High	High
	Baseline	0.0149	1390	---	1551	---			
	-25%	0.011175	1341	-3.53%	1396	-9.99%			
Carbon Fraction of Fuel (ton/kilogram)							Changing the carbon content of fuel is dependent on the market share of its consumption. Considering this, policies aimed at the carbon content of gasoline will have an immediate and high impact because of the extensive gasoline vehicle population. Conversely, doing the same to diesel, E85, and grid electricity will not have a short term effect, but possibly a long term impact if those vehicle types increase in market share. It is also important to note that this assessment is strictly confined to LDVs. Changing the carbon content of grid electricity would have immediate effects on other economic sectors and altering diesel would do the same for freight trucks.		
Gasoline	25%	1.07875	1639	17.91%	1803	16.25%		High	High
	Baseline	0.863	1390	---	1551	---			
	-25%	0.64725	1139	-18.06%	1298	-16.31%			
Diesel	25%	1.08125	1427	2.66%	1608	3.68%		None	Low
	Baseline	0.865	1390	---	1551	---			
	-25%	0.64875	1353	-2.66%	1495	-3.61%			
E85	25%	0.6525	1390	0.00%	1552	0.06%		None	Low
	Baseline	0.522	1390	---	1551	---			
	-25%	0.3915	1390	0.00%	1551	0.00%			
Carbon Per kWh (ton/kilowatt-hour)	25%	0.00075	1390	0.00%	1551	0.00%		None	Low
	Baseline	0.0006	1390	---	1551	---			
	-25%	0.00045	1390	0.00%	1551	0.00%			
Change in Grid Electricity Price (percent)	25%	0.25	1390	0.00%	1551	0.00%	The annual change in price of fuels is shown to have an impact in both consumer driving habits as well as the vehicle types purchased. The price of the fuel must be significant enough to cause a consumer reaction, though. For instance, *Change in Gasoline Price* has a higher impact over time as more and more consumers change to alternative fuel vehicles. Also, the effect of price is constrained by the other vehicle attribute variables taken into consideration by consumers. Electricity may cost less, but the significant up front cost of PHEVs inhibits their market penetration.	None	None
	Baseline	0	1390	---	1551	---			
	-25%	-0.25	1390	0.00%	1550	-0.06%			
Change in Liquid Fuel Price (percent)									
Gasoline	25%	0.02575	1384	-0.43%	1579	1.81%		Low	High
	Baseline	0.0206	1390	---	1551	---			
	-25%	0.01545	1397	0.50%	1518	-2.13%			
Diesel	25%	0.02775	1390	0.00%	1551	0.00%		None	Low
	Baseline	0.0222	1390	---	1551	---			
	-25%	0.01665	1390	0.00%	1553	0.13%			
E85	25%	0.01925	1390	0.00%	1552	0.06%		None	Low
	Baseline	0.0154	1390	---	1551	---			
	-25%	0.01155	1390	0.00%	1546	-0.32%			

The same conclusion is not true for *Annual Change in VMT*, which represents the annual addition of VMT aside from a change caused by the rebound effect. Vehicle travel is important to policy makers because it is the direct source of the majority of LDV emissions. Many policies, ranging from increasing the use of public transportation to taxing fuel use, aim to reduce travel.

The Federal Highway Administration reports that since 1980, total LDV VMT has grown an average of about 2% annually, so +/- 2% are considered reasonable bounds for analysis (FHWA, 2009a). Interestingly, Figure 68 shows that gradual emission reductions are met under a no growth scenario because consumers are traveling less in response to fuel prices rising in the base case. A significant reduction (over 50% by 2030) in total emissions is met at the lower bounds of the simulation though, representing the high impact VMT-focused policies can have.

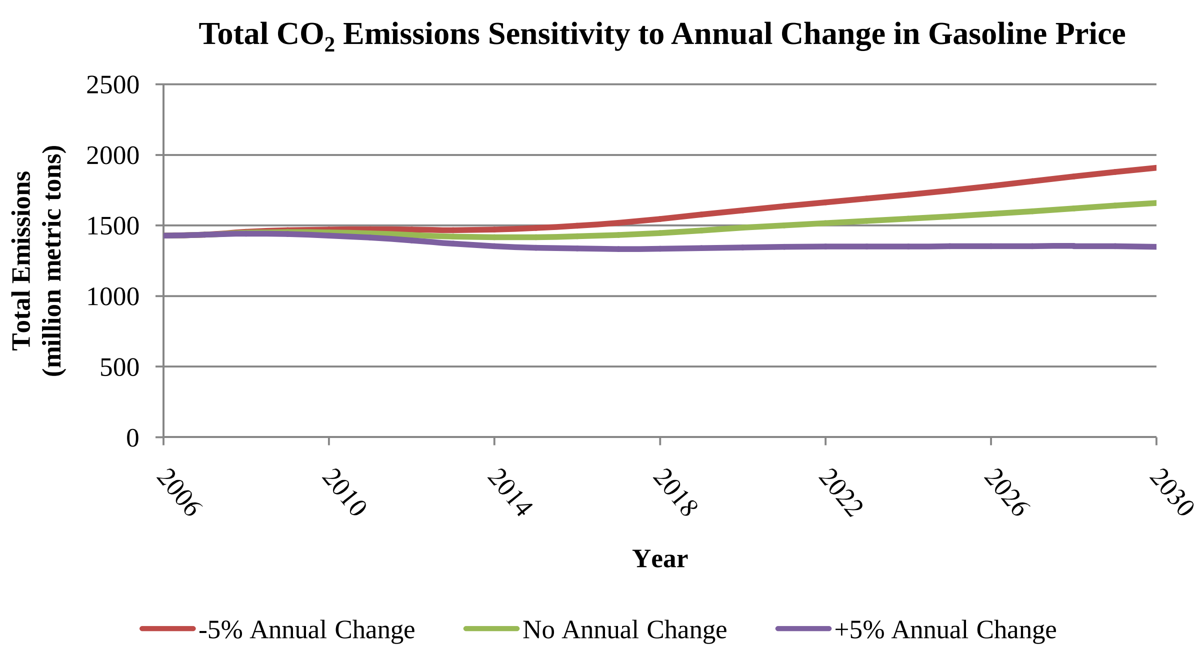

Figure 69 Sensitivity Analysis: Response of total CO_2 emissions to changes in the price of gasoline.

Lastly, the price of gasoline is a commonly cited policy lever for reducing transportation emissions (Metcalf et al., 2008). The cost per gallon of fuel can vary widely on a weekly and monthly basis, but in times of sustained increase (e.g. 2008), consumers have reduced vehicle travel (FHWA, 2009a).

Figure 69 illustrates the annual change in gasoline prices over a range of +/- 5%. The price increase scenario is significant because emissions stabilize compared to the almost 1/3 increase in emissions in the decreasing price case. Though not as drastic as the VMT case, the US federal government imposing gasoline price policies does produce a moderate impact.

Appendix 4.2 Vehicle Attribute Variables

Table 12 outlines exogenous vehicle attribute variables from the consumer choice submodel selected for sensitivity analysis. Boolean variables, such as *Home Refueling for Electric Vehicles* (e.g. values set as 'on' or 'off'), were not analyzed. Also, variables assumed to not significantly change over time, such as *Acceleration* and *Top Speed*, were not included. AEO 2009 Update data was used to assess whether new technologies would lead to meaningful change in these attributes, providing a more realistic analysis.

Instead of directly comparing total emissions, the market share of new purchases is used. Though emission reductions are the goal of policies aimed at increasing the sales of alternative fuel vehicles, these effects will be delayed due to system inertia in turning over the vehicle population. With this in mind, a more immediate effect will be increased sales share, therefore making for a more explicit comparison.

Variable perturbations are made across vehicle types, so changes are consistent for all classes. CLIMATS calculates vehicle class shares exogenously, so model perturbations will not directly affect class values over time, making this simplification necessary.

Sensitivity analysis results show that *Vehicle Price Growth* has the highest impact on new sales market share across all types. Policies such as subsidies for alternative fuel vehicles have the greatest possibility of greater market penetration. An annual 1% decrease in vehicle price can lead to a 23% to 110% increase in market share of selected vehicle types by 2015. The effects of this high impact change on total CO_2 emissions can differ though.

Figure 70 illustrates that a decrease in price for gasoline vehicles can lead to a gradual, long term increase in emissions. Conversely, policies that increase the price of fossil fuel vehicles, such as feebates, must be greater than 1% annually to lead to a decrease in emissions. These price effects are localized to only gasoline vehicles and do not represent a consequent decrease in price for alternative fuel vehicles called for by a feebate program (Greene et al., 2005).

Table 12 Sensitivity analysis of select vehicle attribute variables.

Variable	Values		2015 Sales Market Share	2015 % Difference	2030 Sales Market Share	2030 % Difference	Rationale	Short Term Leverage	Long Term Leverage
Fuel Economy Growth(miles per gallon)									
CGV	0%	0	68.0%	-2.44%	62.8%	-13.38%	The annual change in fuel economy is shown to have a high impact on specific vehicle types. Types more closely constrained by higher new retail prices, such as PHEVs, are less effected by positive changes. On the other hand, gasoline vehicles gain market share in the long term because consumers are more likely to stay with a commonly used technology than switch to alternative fuels, given that gasoline vehicles become more fuel efficient. The highest percentage impact is achieved by diesel vehicles and FFVs. where the reduction in fuel cost due to a higher fuel economy is enough to reduce the impact on consumer utility of lower fuel availability and price. In the absence of changes in fuel economy to gasoline vehicles, this analysis shows the possibility of increasing the market share of some alternative fuel vehicles with moderate, but consistant changes in technology. Other, more cost prohibitive, technologies like grid electric are more ineleastic to technology changes and may require additional policy aid.	Low	High
	Baseline	---	69.7%	---	72.5%	---			
	2%	0.02	73.7%	5.74%	80.1%	10.48%			
Diesel	0%	0	19.0%	4.40%	22.3%	-0.45%		High	High
	Baseline	---	18.2%	---	22.4%	---			
	2%	0.02	21.5%	18.13%	54.8%	144.64%			
HEV	0%	0	6.0%	-28.40%	5.1%	-60.47%		High	High
	Baseline	---	8.4%	---	12.9%	---			
	2%	0.02	7.9%	-5.73%	12.3%	-4.65%			
PHEV	0%	0	0.0007%	0.00%	0.009%	-95.91%		None	None
	Baseline	---	0.0%	---	0.2%	---			
	2%	0.02	0.0009%	0.00%	0.049%	-78.87%			
FFV	0%	0	5.6%	52.59%	4.9%	10.86%		High	High
	Baseline	---	3.7%	---	4.4%	---			
	2%	0.02	7.3%	98.91%	11.8%	166.97%			
Vehicle Price Growth (2007 $)									
CGV	1%	0.01	51.0%	-26.83%	16.0%	-77.93%	*Vehicle Price Growth* represents a very high impact and direct method of changing the market share of different vehicle types. Across all types, a gradual 1% decrease in price drastically increases the number of vehicles purchased each year and vice versa for a gradual 1% increase. The impact is also significantly seen both in the short and long term, making this a key policy lever in the model.	High	High
	Baseline	---	69.7%	---	72.5%	---			
	-1%	-0.01	85.8%	23.10%	95.0%	31.03%			
Diesel	1%	0.01	7.6%	-58.24%	2.0%	-91.07%		High	High
	Baseline	---	18.2%	---	22.4%	---			
	-1%	-0.01	33.9%	86.26%	65.0%	190.18%			
HEV	1%	0.01	3.3%	-60.62%	1.0%	-92.25%		High	High
	Baseline	---	8.4%	---	12.9%	---			
	-1%	-0.01	14.0%	67.06%	33.0%	155.81%			
PHEV	1%	0.01	0.000%	0.00%	0.000%	-100.00%		None	High
	Baseline	---	0.0%	---	0.2%	---			
	-1%	-0.01	0.000%	0.00%	45.0%	19465%			
FFV	1%	0.01	1.5%	-59.13%	0.0%	-100.00%		High	High
	Baseline	---	3.7%	---	4.4%	---			
	1%	-0.01	7.7%	109.81%	25.0%	465.61%			

Variable	Values		2015 Sales Market Share	2015 % Difference	2030 Sales Market Share	2030 % Difference	Rationale	Short Term Leverage	Long Term Leverage
Maintenance Cost Growth (2007 $)									
CGV	1%	0.01	68.1%	-2.30%	63.8%	-12.00%	The *Maintenance Cost Growth* variables represents the annual change in the cost of repairing a vehicle. The literature suggests that consumers make purchasing decisions based on the yearly cost of maintaining a vehicle verse purchasing a new model, among other decisions. This impact is shown clearly in this analysis. Consumers are less likely to switch to alternative fuel vehicles if the cost of repairing traditional gasoline vehicles decreases. Reducing the cost of repairs *for* alternative fuel vehicles also has a low to moderate impact in both the short and long term as to whether consumers choose to purchase them. An important point to make is that HEVs are more susceptible to the impacts of maintenance due to the high cost of battery replacement. In fact, the analysis shows that even an annual 1% reduction in costs may not be enough to increase its market share.	Low	High
	Baseline	0	69.7%	---	72.5%	---			
	-1%	-0.01	71.3%	2.30%	72.6%	0.14%			
Diesel	1%	0.01	16.1%	-11.54%	14.7%	-34.38%		High	High
	Baseline	0	18.2%	---	22.4%	---			
	-1%	-0.01	19.4%	6.59%	22.7%	1.34%			
HEV	1%	0.01	6.2%	-26.37%	5.6%	-56.28%		High	High
	Baseline	0	8.4%	---	12.9%	---			
	-1%	-0.01	7.1%	-14.92%	8.6%	-33.33%			
PHEV	1%	0.01	0.000%	0.00%	0.000%	-99.96%		None	None
	Baseline	0	0.0%	---	0.2%	---			
	-1%	-0.01	0.000%	0.00%	0.008%	-96%			
FFV	1%	0.01	5.4%	47.68%	4.6%	3.62%		High	High
	Baseline	0	3.7%	---	4.4%	---			
	-1%	-0.01	6.2%	67.85%	6.7%	50.45%			
Range Growth(miles)									
CGV	1%	0.01	69.9%	0.29%	69.0%	-4.83%	Changing a vehicles range per tank of fuel will have a limited impact on market share. The analysis shows that only in the case of FFVs and HEVs, which are limited by fuel availability and battery charge respectively, can range be effective in increasing sales.	None	Low
	Baseline	---	69.7%	---	72.5%	---			
	-1%	-0.01	69.8%	0.14%	68.7%	-5.24%			
Diesel	1%	0.01	17.8%	-2.20%	18.4%	-17.86%		None	Low
	Baseline	---	18.2%	---	22.4%	---			
	-1%	-0.01	17.7%	-2.75%	18.3%	-18.30%			
HEV	1%	0.01	6.7%	-20.53%	7.2%	-44.34%		Low	Low
	Baseline	---	8.4%	---	12.9%	---			
	-1%	-0.01	6.6%	-20.76%	7.1%	-44.88%			
PHEV	1%	0.01	0.000%	0.00%	0.001%	-99.52%		None	None
	Baseline	---	0.0%	---	0.2%	---			
	-1%	-0.01	0.000%	0.00%	0.001%	-100%			
FFV	1%	0.01	5.8%	58.31%	5.7%	28.96%		Low	Low
	Baseline	---	3.7%	---	4.4%	---			
	-1%	-0.01	5.8%	57.22%	5.6%	25.79%			

Variable	Values		2015 Total Emissions Values	2015 % Difference	2030 Total Emissions Values	2030 % Difference	Rationale	Short Term Leverage	Long Term Leverage
Fuel Availability (%)									
Diesel	0%	0.3125	1388	-0.14%	1571	1.29%	*Fuel Availability* could be a key determinate in whether a consumer purchases an alternative fuel vehicle. For instance, E85 is not widely available at fuel stations, so consumers are less likely to purchase vehicles that use it. The analysis shows a low, short and long term impact of on total emissions though. Individual policies, such as renewable fuel standards, will not significantly impact emissions, but may play a complimentary role in making alternative fuel vehicles more attractive to consumers.	Low	Low
	Baseline	0.25	1390	---	1551	---			
	100%	0.1875	1358	-2.30%	1534	-1.10%			
E85	0%	0.025	1388	-0.14%	1571	1.29%		Low	Low
	Baseline	0.02	1390	---	1551	---			
	100%	0.015	1341	-3.53%	1486	-4.19%			

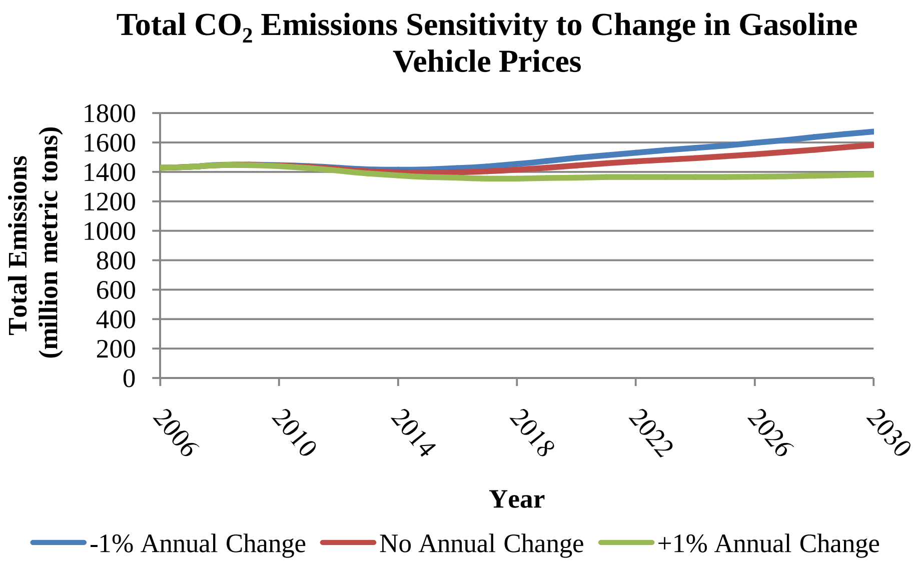

Figure 70 Sensitivity Analysis: Response of total CO_2 emissions to changes in gasoline vehicle price.

Figure 71 represents a more pronounced long term increase in total emissions, even with a decrease in diesel vehicle prices. This is important for policy making because the increase in emissions continues as diesel vehicles reach a 65% market share of new vehicle purchases. Individual policies aimed at increasing the use of diesel vehicles may not lead to emission reductions.

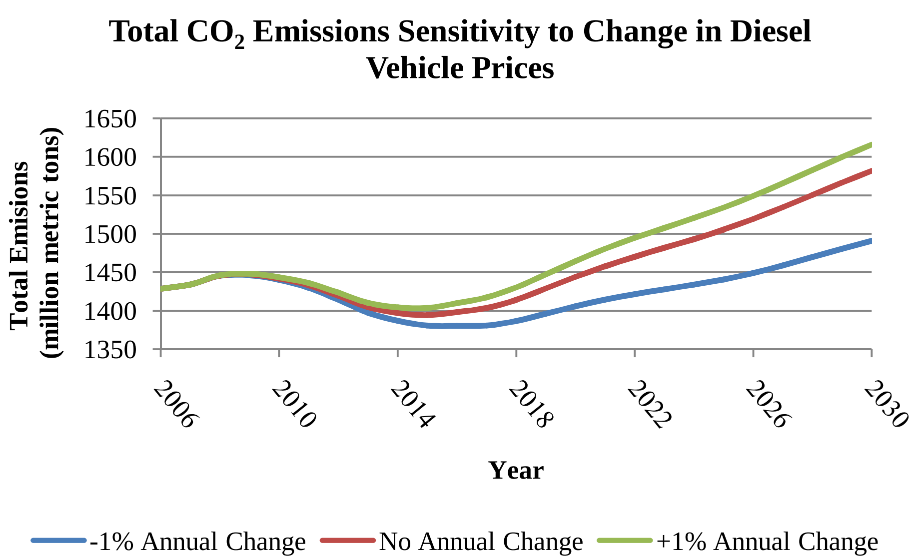

Figure 71 Sensitivity Analysis: Response of total CO_2 emissions to changes in diesel vehicle price.

Figure 72 and Figure 74 shows much of the same story with HEVs and FFVs. A 1% annual decrease in price does lead to a decrease in yearly emissions compared to the base case, but it does not stabilize or decrease emission trends. Large price breaks or complimentary efforts may be needed when formulating policies around these vehicle types.

Small, long term reductions can be reached, though, by decreasing the price of PHEVs. Figure 73 shows that just a 12% PHEV share in new sales can lead to emission cuts, so policies aimed at electric battery vehicles may produce more immediate results when compared to other alternative fuel vehicles.

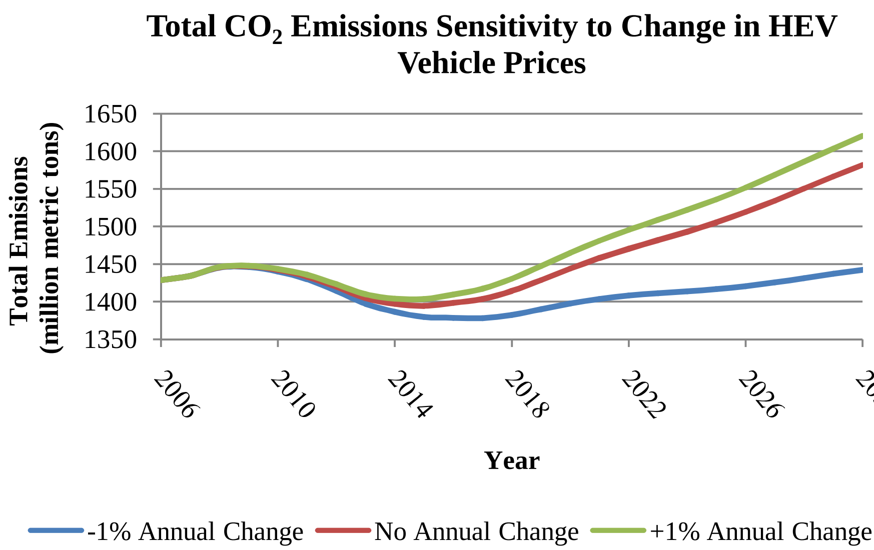

Figure 72 Sensitivity Analysis: Response of total CO_2 emissions to changes in HEV price.

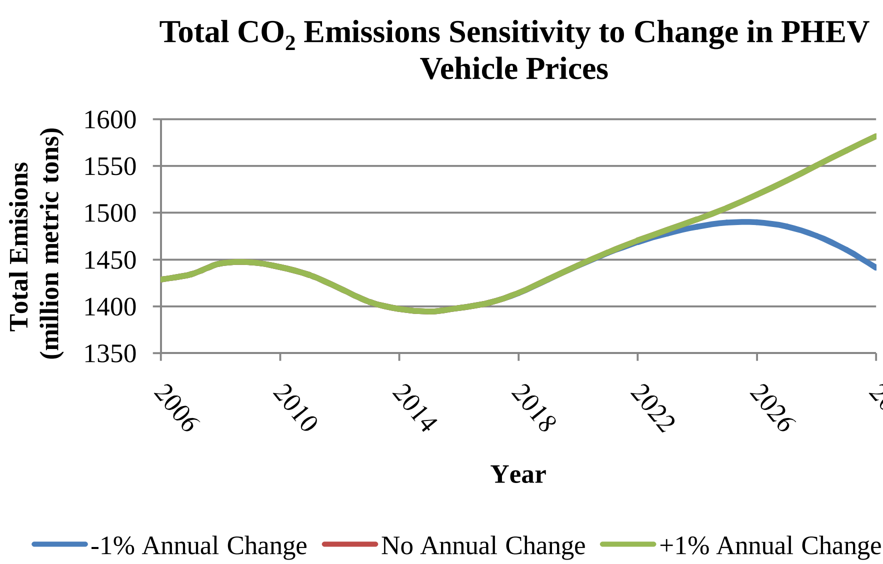

Figure 73 Sensitivity Analysis: Response of total CO_2 emissions to changes in PHEV price.

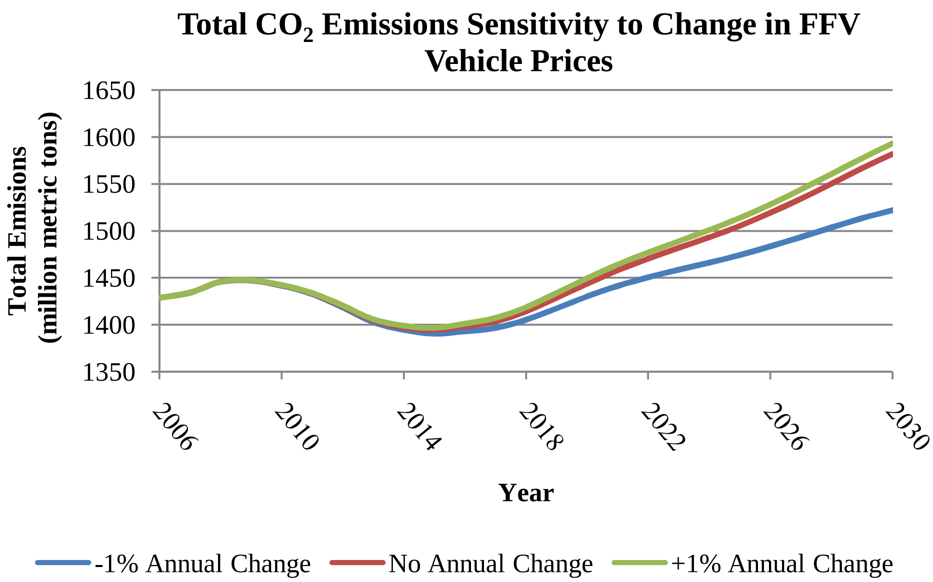

Figure 74 Sensitivity Analysis: Response of total CO_2 emissions to changes in FFV price.

Appendix 5 Model Analysis Scenario Details

The following tables detail the input data used to create model scenarios. *Appendix 5.1* details specific user input variables used to control annual trends, emissions factors, and policy implementation. *Appendix 5.2* details initialization data used to simulate the US light duty vehicle sector and more accurately assess policy impacts. *Appendix 5.3* details vehicle attributes used in the consumer decision making submodel for each scenario.

Appendix 5.1 User Input Variables for Model Scenarios

Appendix 5.1.1 Fuel Specifications

Fuel specifications were taken from the assumptions used in the GREET model as well as those used in the Energy Information Administration Annual Energy Outlook (EIA, 2008b; Wang, 1996)

Fuel Specifications *(used for all scenarios)*			
	Fuel Density *(kilograms/gallon)*	Fuel Energy Content *(Btu/gallon)*	Carbon Fraction of Fuel *(ton/kg)*
Gasoline	2.891	115400	0.863
Diesel	3.167	128700	0.865
E85	2.988	81621.5	0.522
Electricity	0	3412	.0006 *(ton/kWh)*

Appendix 5.1.2 Model Growth Factors

Model Growth Factors				
	AEO Validation Scenario	Policy Scenario #1	Policy Scenario #2	Policy Scenario #3
Annual Change in Sales *(percent)*	1.13%	1.13%	1.13%	1.13%
Annual Growth in VMT *(percent)*	1.49%	1.49%	1.49%	1.49%
Change in Grid Electricity Price *(percent)*	.45%	.45%	.45%	.45%
Change in Liquid Fuel Price *(percent)*	G- 2.06% D- 2.22% E85- 1.54%	G- 2.06% D- 2.22% E85- 1.54%	G- 2.06% D- 2.22% E85- 1.54%	G- 2.06% D- 2.22% E85- 1.54%

Appendix 5.1.3 System Feedback Variables

Model Feedback Values				
	AEO Validation Scenario	Policy Scenario #1	Policy Scenario #2	Policy Scenario #3
Elasticity of VMT FC Per Mile	10%	10%	10%	10%
Rebound Effect Switch	0 and 1	1	1	1
Scrappage-VMT Feedback Switch	0 and 1	1	1	1

Appendix 5.1.4 Upstream Fuel Emissions Values

Upstream fuel emission factors are taken from the GREET model assumptions (Wang, 1996).

Upstream Fuel Emissions Values *(used for all scenarios)*		
Vehicle Fuel Type	Fuel Production Factors *(ton/gallon)*	Feedstock Factors *(ton/gallon)*
Gasoline	67	17
Diesel	43	21
Grid Independent Hybrid Electric	67	12
Plug in Hybrid Electric	45	12
Gasoline-E85 Flex Fuel	180	-209

Appendix 5.1.5 EPA Fuel Economy Degradation Factors

The reduction in fuel economy from the vehicles published sticker value due to more rigorous driving habits than those used tested by the EPA has been well documented. The Energy Information Administration published the below values which takes into account a small increase in the performance of the EPA tests (EIA, 2007b).

EPA Fuel Economy Degradation Factor *(in percent of fuel economy sticker value)*			
Model Increment	Model Year	All Automobile Classes	All Truck Classes
0	2006	78.7	84.0
1	2007	81.5	84.0
2	2008	81.6	84.0
3	2009	81.7	84.0
4	2010	81.8	84.0
5	2011	81.9	84.0
6	2012	82.0	84.0
7	2013	82.1	84.0
8	2014	82.2	84.0
9	2015	82.3	84.0
10	2016	82.4	84.0
11	2017	82.5	84.0
12	2018	82.6	84.0
13	2019	82.7	84.0
14	2020	82.8	84.0
15	2021	82.9	84.0
16	2022	83.0	84.0
17	2023	83.1	84.0
18	2024	83.2	84.0
19	2025	83.3	84.0
20	2026	83.4	84.0
21	2027	83.5	84.0
22	2028	83.6	84.0
23	2029	83.7	84.0
24	2030	83.8	84.0

Appendix 5.2 Model Initialization Variables

Appendix 5.2.1 Vehicle Class Classifications

Classifications are taken from Environmental Protection Agency regulations, which are commonly used in transportation policy analysis. Gross Vehicle Weight Rating (GVWR) is defined as the curb weight of the vehicle plus carrying capacity. Interior volume is defined as the combined passenger and cargo volume.

Vehicle Class	Classification Description
Sub Compact Car	Interior volume between 85 – 99.9 cubic feet
Compact Car	Interior volume between 100 – 109.9 cubic feet
Mid Size Car	Interior volume between 110 – 119.9 cubic feet
Large Car	Interior volume greater than 120 cubic feet
Small SUV	GVWR less than 6,000 lbs.
Large SUV	GVWR between 6,000 – 8,500 lbs.
Small Pickup Truck	GVWR less than 6,000 lbs.
Large Pickup Truck	GVWR between 6,000 – 8,500 lbs.

Appendix 5.2.2 Initial Vehicle Population by Cohort

Historic vehicle population data is not readily available by class and fuel type. The EPA annually produces vehicle sales by year in the Light Duty Automotive Technology and Fuel Economy Trends report (EPA, 2008). This sales data was used as the maximum estimate of historic vehicle population by class, fuel type, and cohort. Using total light duty vehicle population estimates made in the Transportation Energy Data Book, these sales data were reduced to match published total values.

Initial Vehicle Population, 1986-2006 (*used for all scenarios, by cohort)*

Vehicle Fuel Type	Vehicle Class	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Conventional Gasoline	Sub Compact Car	1098	1500	1500	1614	1575	644	800	1382	1601	1487	1108	1123	1095	1072	500	1000	600	300	100	50	50
	Compact Car	2819	3094	2921	2812	2998	2197	2612	2368	2126	1840	1000	1432	1302	1173	1221	500	500	300	300	200	100
	Mid Size Car	3113	2886	3022	2983	2807	2480	2984	2141	2967	1399	1359	1515	1157	1330	1120	1000	450	291	113	10	10
	Large Car	1570	1834	1885	1861	1852	1416	1665	1559	912	1195	1066	1305	1277	1103	1240	1012	300	489	203	78	50
	Small SUV	3757	3085	4711	4117	3191	2449	2641	2830	1880	1448	1889	1415	1023	1011	850	400	253	339	397	220	100
	Large SUV	327	490	634	654	453	781	825	721	388	200	281	273	203	66	80	92	0	0	0	0	0
	Small Pick-up Truck	1500	1959	1984	1821	1973	1525	1832	1587	1732	1559	1500	1285	1231	1035	587	150	100	300	0	0	0
	Large Pick-up Truck	1938	1939	1621	1853	1806	1192	781	958	683	849	454	485	238	266	244	141	224	130	65	0	0
Diesel	Sub Compact Car	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Compact Car	83	78	113	99	108	123	109	126	35	102	79	86	79	68	57	50	50	50	0	0	0
	Mid Size Car	62	71	87	66	79	75	74	100	27	55	44	41	34	35	27	10	0	0	0	0	0
	Large Car	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Small SUV	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Large SUV	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Small Pick-up Truck	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Large Pick-up Truck	47	51	68	46	49	57	44	50	12	36	19	21	21	15	11	10	0	0	0	0	0
Grid Independent Hybrid Electric	Sub Compact Car	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Compact Car	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Mid Size Car	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Large Car	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Small SUV	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Large SUV	74	58	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Small Pick-up Truck	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Large Pick-up Truck	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Plug in Hybrid Electric	Sub Compact Car	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Compact Car	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Mid Size Car	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Large Car	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Small SUV	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Large SUV	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Small Pick-up Truck	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Large Pick-up Truck	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Gasoline-E85 Flex Fuel	Sub Compact Car	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Compact Car	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Mid Size Car	39	38	37	31	28	23	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Large Car	19	7	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Small SUV	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Large SUV	5	4	4	2	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Small Pick-up Truck	26	22	18	17	15	13	11	3	1	1	0	0	0	0	0	0	0	0	0	0	0
	Large Pick-up Truck	50	42	34	33	30	24	21	6	3	2	0	0	0	0	0	0	0	0	0	0	0

Appendix 5.2.3 Initial Fuel Economy by Cohort

The EPA Light Duty Automotive Technology and Fuel Economy Trends report was used to estimate average fuel economy for each vehicle class/ vehicle fuel type (EPA, 2008).

Initial Fuel Economy, 1986-2006 (*used for all scenarios, by cohort)*

Vehicle Fuel Type	Vehicle Class	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Conventional Gasoline	Sub Compact Car	27.3	26.8	28.2	28.4	30.7	31.3	31.3	31.6	32.5	32.9	31.5	31.6	32	31.8	26.2	26.3	26.1	26.9	26.3	26.5
	Compact Car	32.7	31.9	32.1	31.8	31.7	30.5	30.1	30.9	30.3	30.3	30.6	29.8	29.6	28.6	29	28	28	27	26	26
	Mid Size Car	29.8	28.7	28.3	27.7	27.2	27	27.1	27.1	26.5	26.5	26.1	25.9	26.1	25.8	22.8	22.1	22.5	22.6	22.1	22
	Large Car	26.4	26	26	26	25.4	25.6	24.8	24.6	24.5	24.3	24.4	24.1	24.2	23.8	21.8	20	20.4	20.6	20.3	20
	Small SUV	21.9	21.3	21.2	20.9	23.1	20.3	20.5	20.4	20.4	20.2	19.8	20	20.1	20.1	18.9	19.5	19.1	20.4	20.4	18.8
	Large SUV	14.2	14.3	14.3	14.5	14.3	13.8	13.6	13.6	13.1	13.6	14.1	14.1	14.	14.4	14.4	14	14	14	14	14
	Small Pick-up Truck	22.3	22.1	22.1	21.2	21.5	21.8	21.9	22.8	22.7	22.8	22.3	22.6	22.4	22.2	21.7	21.7	21.5	21.5	21.5	21.5
	Large Pick-up Truck	18.7	18.5	18.4	18.2	18.1	18.2	17.6	17.3	17.8	17.1	16.8	17	16.9	16.7	14	14	14	14	14	14
Diesel	Sub Compact Car	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Compact Car	44	44	44	43	43	43	43	42	42	42	42	41	41	41	40	40	40	40	40	40
	Mid Size Car	39	39	39	38	38	38	37	37	37	37	37	36	36	36	35	35	35	35	35	35
	Large Car	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Small SUV	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Large SUV	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Small Pick-up Truck	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Large Pick-up Truck	28	28	28	27	27	27	26	26	26	26	26	26	25	25	24	23	23	23	23	23
Grid Independent Hybrid Electric	Sub Compact Car	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Compact Car	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Mid Size Car	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Large Car	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Small SUV	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Large SUV	41	41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Small Pick-up Truck	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Large Pick-up Truck	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Plug in Hybrid Electric	Sub Compact Car	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Compact Car	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Mid Size Car	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Large Car	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Small SUV	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Large SUV	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Small Pick-up Truck	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Large Pick-up Truck	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Gasoline-E85 Flex Fuel	Sub Compact Car	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Compact Car	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Mid Size Car	23	23	23	23	23	23	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Large Car	22	22	22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Small SUV	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Large SUV	19	19	19	19	19	19	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Small Pick-up Truck	19	19	19	19	19	19	19	19	19	0	0	0	0	0	0	0	0	0	0	0
	Large Pick-up Truck	18	18	18	18	18	18	18	18	18	0	0	0	0	0	0	0	0	0	0	0

Appendix 5.2.4 Initial Annual Miles Traveled per Vehicle by Cohort

Annual vehicle VMT values were taken from the Department of Energy Transportation Energy Data Book, Table 3.7 (Davis and Diegal, 2007).

Initial Annual Miles Traveled Per Vehicle By Cohort		
Cohort	All Automobile Classes	All Truck Classes
0	15000	17500
1	14300	19200
2	13700	19800
3	12900	17900
4	12400	17500
5	12000	17000
6	11700	15600
7	11400	15400
8	11100	15100
9	10700	13200
10	9900	9200
11	9000	9200
12	9400	9200
13	8200	9200
14	7200	9200
15	5300	9200
16	5300	9200
17	5300	9200
18	5300	9200
19	5300	9200
20	5300	9200

Appendix 5.3 Vehicle Attribute Details for Model Scenarios

The following tables represent model scenario values for each vehicle attribute simulated by the consumer choice submodel. It is assumed that *Home Refueling for EVs* and *Multifuel Capability* are always set to '1' ('on') for plug in hybrid electric vehicles and gasoline-E85 flex fuel vehicles respectively, so tables are not explicitly shown.

Appendix 5.3.1 Fuel Economy

Fuel Economy *(miles per gallon)*
Note: First Column = 2006 mpg; second column = annual % change

Vehicle Fuel Type	Vehicle Class	AEO Validation Scenario/S2/S3		Policy Scenario #1				
		Baseline	Annual % Change	Baseline	BAU	Low	Medium	High
Conventional Gasoline	Sub Compact Car	29.8	1.26	29.8	1.26	.01	.02	.03
	Compact Car	33.1	1.04	33.1	1.04	.01	.02	.03
	Mid Size Car	29.6	1.12	29.6	1.12	.01	.02	.03
	Large Car	27.6	1.27	27.6	1.27	.01	.02	.03
	Small SUV	25.7	1.08	25.7	1.08	.01	.02	.03
	Large SUV	20.9	1.12	20.9	1.12	.01	.02	.03
	Small Pick-up Truck	23.1	1.12	23.1	1.12	.01	.02	.03
	Large Pick-up Truck	21.4	0.98	21.4	0.98	.01	.02	.03
Diesel	Sub Compact Car	0	0	0	0	0	0	0
	Compact Car	44.5	0.86	44.5	0.86	0.86	0.86	0.86
	Mid Size Car	39.8	0.97	39.8	0.97	0.97	0.97	0.97
	Large Car	37.0	1.04	37.0	1.04	1.04	1.04	1.04
	Small SUV	34.6	0.81	34.6	0.81	0.81	0.81	0.81
	Large SUV	28.2	0.81	28.2	0.81	0.81	0.81	0.81
	Small Pick-up Truck	31.0	0.84	31.0	0.84	0.84	0.84	0.84
	Large Pick-up Truck	28.8	0.65	28.8	0.65	0.65	0.65	0.65
Grid Independent Hybrid Electric	Sub Compact Car	44.0	1.17	44.0	1.17	1.17	1.17	1.17
	Compact Car	47.8	0.85	47.8	0.85	0.85	0.85	0.85
	Mid Size Car	42.7	0.88	42.7	0.88	0.88	0.88	0.88
	Large Car	0	0	0	0	0	0	0
	Small SUV	0	0	0	0	0	0	0
	Large SUV	30.3	0.87	30.3	0.87	0.87	0.87	0.87
	Small Pick-up Truck	0	0	0	0	0	0	0
	Large Pick-up Truck	0	0	0	0	0	0	0
Plug in Hybrid Electric *(gasoline/electric)*	Sub Compact Car	0	0	0	0	0	0	0
	Compact Car	54.0	0.99	54.0	0.99	0.99	0.99	0.99
	Mid Size Car	55.7	0.37	55.7	0.37	0.37	0.37	0.37
	Large Car	0	0	0	0	0	0	0
	Small SUV	42.5	0.82	42.5	0.82	0.82	0.82	0.82
	Large SUV	0	0	0	0	0	0	0
	Small Pick-up Truck	0	0	0	0	0	0	0
	Large Pick-up Truck	0	0	0	0	0	0	0
Gasoline-E85 Flex Fuel	Sub Compact Car	30.7	1.43	30.7	1.43	1.43	1.43	1.43
	Compact Car	33.4	1.16	33.4	1.16	1.16	1.16	1.16
	Mid Size Car	29.9	1.13	29.9	1.13	1.13	1.13	1.13
	Large Car	27.9	1.27	27.9	1.27	1.27	1.27	1.27
	Small SUV	25.8	1.12	25.8	1.12	1.12	1.12	1.12
	Large SUV	21.1	1.12	21.1	1.12	1.12	1.12	1.12
	Small Pick-up Truck	23.4	1.11	23.4	1.11	1.11	1.11	1.11
	Large Pick-up Truck	21.6	0.97	21.6	0.97	0.97	0.97	0.97

Appendix 5.3.2 New Vehicle Retail Price

New Vehicle Retail Price *(thousands of 2007 $)*
Note: First Column = 2006 retail price; second column = annual % change

Vehicle Fuel Type	Vehicle Class	AEO Validation Scenario		Policy Scenario #1		Policy Scenario #2		Policy Scenario #3	
Conventional Gasoline	Sub Compact Car	27.9	0.28	27.9	0.28	27.9	0.28	27.9	0.28
	Compact Car	22.0	0.28	22.0	0.28	22.0	0.28	22.0	0.28
	Mid Size Car	28.0	0.25	28.0	0.25	28.0	0.25	28.0	0.25
	Large Car	34.1	0.22	34.1	0.22	34.1	0.22	34.1	0.22
	Small SUV	25.3	0.27	25.3	0.27	25.3	0.27	25.3	0.27
	Large SUV	36.0	0.20	36.0	0.20	36.0	0.20	36.0	0.20
	Small Pick-up Truck	17.3	0.42	17.3	0.42	17.3	0.42	17.3	0.42
	Large Pick-up Truck	22.0	0.30	22.0	0.30	22.0	0.30	22.0	0.30
Diesel	Sub Compact Car	0	0	0	0	0	0	0	0
	Compact Car	23.5	0.20	23.5	0.20	23.5	0.20	23.5	0.20
	Mid Size Car	29.3	0.21	29.3	0.21	29.3	0.21	29.3	0.21
	Large Car	36.0	0.11	36.0	0.11	36.0	0.11	36.0	0.11
	Small SUV	27.6	0.21	27.6	0.21	27.6	0.21	27.6	0.21
	Large SUV	38.3	0.14	38.3	0.14	38.3	0.14	38.3	0.14
	Small Pick-up Truck	20.7	0.04	20.7	0.04	20.7	0.04	20.7	0.04
	Large Pick-up Truck	24.8	0.12	24.8	0.12	24.8	0.12	24.8	0.12
Grid Independent Hybrid Electric	Sub Compact Car	28.1	-0.01	28.1	-0.01	28.1	-0.01	28.1	-0.01
	Compact Car	25.5	0.02	25.5	0.02	25.5	0.02	25.5	0.02
	Mid Size Car	31.7	0.01	31.7	0.01	31.7	0.01	31.7	0.01
	Large Car	0	0	0	0	0	0	0	0
	Small SUV	0	0	0	0	0	0	0	0
	Large SUV	29.3	-0.03	29.3	-0.03	29.3	-0.03	29.3	-0.03
	Small Pick-up Truck	0	0	0	0	0	0	0	0
	Large Pick-up Truck	0	0	0	0	0	0	0	0
Plug in Hybrid Electric	Sub Compact Car	0	0	0	0	0	0	0	0
	Compact Car	28.4	-0.28	28.4	-0.28	28.4	-0.28	28.4	-0.28
	Mid Size Car	33.6	-0.03	33.6	-0.03	33.6	-0.03	33.6	-0.03
	Large Car	0	0	0	0	0	0	0	0
	Small SUV	41.2	-0.26	41.2	-0.26	41.2	-0.26	41.2	-0.26
	Large SUV	0	0	0	0	0	0	0	0
	Small Pick-up Truck	0	0	0	0	0	0	0	0
	Large Pick-up Truck	0	0	0	0	0	0	0	0
Gasoline-E85 Flex Fuel	Sub Compact Car	26.7	0.02	26.7	0.02	26.7	0.02	26.7	0.02
	Compact Car	23.8	-0.01	23.8	-0.01	23.8	-0.01	23.8	-0.01
	Mid Size Car	28.7	0.20	28.7	0.20	28.7	0.20	28.7	0.20
	Large Car	35.3	0.12	35.3	0.12	35.3	0.12	35.3	0.12
	Small SUV	25.8	0.25	25.8	0.25	25.8	0.25	25.8	0.25
	Large SUV	36.4	0.20	36.4	0.20	36.4	0.20	36.4	0.20
	Small Pick-up Truck	20.2	0.11	20.2	0.11	20.2	0.11	20.2	0.11
	Large Pick-up Truck	23.9	0.06	23.9	0.06	23.9	0.06	23.9	0.06

Appendix 5.3.3 Other Vehicle Attribute Variable Inputs

Vehicle Attribute Variable Inputs – All Scenarios (Second column = annual change if necessary)

Vehicle Fuel Type	Vehicle Class	Market Penetration	Acceleration *(0-60, in seconds)*	Fuel Availability		Luggage Space *(cubic feet)*	Maintenance Cost (2007 $)		Make/Model Availability		Range *(miles)*		Top Speed *(miles per hour)*
Conventional Gasoline	Sub Compact Car	2006	9	1	0	12	917	0	35	.01	441	1.25	115
	Compact Car	2006	10	1	0	13	917	0	35	.01	876	1.06	115
	Mid Size Car	2006	9	1	0	14	917	0	35	.01	521	1.11	115
	Large Car	2006	8	1	0	15	917	0	35	0	509	1.27	115
	Small SUV	2006	11	1	0	15	917	0	35	0	475	1.09	115
	Large SUV	2006	10	1	0	15	917	0	35	0	523	1.14	115
	Small Pick-up Truck	2006	10	1	0	15	917	0	35	0	485	1.16	115
	Large Pick-up Truck	2006	10	1	0	15	917	0	35	0	601	1.02	115
Diesel	Sub Compact Car	0	0	0	0	0	0	0	0	0	0	0	0
	Compact Car	2006	10	.25	.01	13	1375	0	4	.02	1183	1.06	110
	Mid Size Car	2006	9	.25	.01	14	1375	0	4	.02	703	1.11	110
	Large Car	2007	8	.25	.01	15	1375	0	4	.02	681	1.34	110
	Small SUV	2006	11	.25	.01	15	1375	0	4	.02	640	1.09	110
	Large SUV	2006	10	.25	.01	15	1375	0	4	.02	703	1.14	110
	Small Pick-up Truck	2007	10	.25	.01	15	1375	0	8	.02	651	1.22	110
	Large Pick-up Truck	2006	10	.25	.01	15	1375	0	8	.02	805	1.02	110
Grid Independent Hybrid Electric	Sub Compact Car	2011	9	1	0	10	1146	0	5	.05	571	1.39	90
	Compact Car	2006	10	1	0	11	1146	0	5	.05	1096	1.06	90
	Mid Size Car	2006	9	1	0	12	1146	0	5	.05	652	1.11	90
	Large Car	0	0	0	0	0	0	0	0	0	0	0	0
	Small SUV	0	0	0	0	0	0	0	0	0	0	0	0
	Large SUV	2006	10	1	0	13	1146	0	5	.05	654	1.14	90
	Small Pick-up Truck	0	0	0	0	0	0	0	0	0	0	0	0
	Large Pick-up Truck	0	0	0	0	0	0	0	0	0	0	0	0
Plug in Hybrid Electric	Sub Compact Car	0	9	1	0	0	1834	0	0	0	0	0	0
	Compact Car	2010	10	1	0	13	1834	0	1	.01	1139	1.13	90
	Mid Size Car	2015	9	1	0	14	1834	0	1	.01	779	0.58	90
	Large Car	0	0	0	0	0	0	0	0	0	0	0	0
	Small SUV	2010	11	1	0	15	1834	0	1	.01	628	1.08	90
	Large SUV	0	0	0	0	0	0	0	0	0	0	0	0
	Small Pick-up Truck	0	0	0	0	0	0	0	0	0	0	0	0
	Large Pick-up Truck	0	0	0	0	0	0	0	0	0	0	0	0
Gasoline-E85 Flex Fuel	Sub Compact Car	2011	9	.02	.005	12	917	0	2	.02	398	1.39	115
	Compact Car	2009	10	.02	.005	13	917	0	2	.02	774	1.15	115
	Mid Size Car	2006	9	.02	.005	14	917	0	2	.02	455	1.11	115
	Large Car	2006	8	.02	.005	15	917	0	2	.02	443	1.27	115
	Small SUV	2007	11	.02	.005	15	917	0	2	.02	410	1.14	115
	Large SUV	2006	10	.02	.005	15	917	0	2	.02	448	1.14	115
	Small Pick-up Truck	2006	10	.02	.005	15	917	0	2	.02	417	1.16	115
	Large Pick-up Truck	2006	10	.02	.005	15	917	0	2	.02	506	1.02	115

Appendix 5.3.4 Consumer Utility Function Vehicle Attribute Coefficients

Vehicle Class	Vehicle Price	Fuel Cost	Range	Top Spee d	Acceler ation	Multifuel Capability	Home Refueling for EVs	Maintenance Cost	Luggage Space	Fuel Availability 1	Fuel Availability 2	Make/Model Availability
Sub Compact Car	-0.00038	-0.1470	-24.5119	.022	-0.155	0.000541	0.02945	-0.00094	0.075	-0.92879	-10.9861	0.37
Compact Car	-0.00035	-0.1470	-24.5119	.022	-0.155	0.000541	0.02945	-0.00094	0.075	-0.92879	-10.9861	0.37
Mid Size Car	-0.00031	-0.1470	-24.5119	.022	-0.155	0.000541	0.02945	-0.00094	0.075	-0.92879	-10.9861	0.37
Large Car	-0.00026	-0.1470	-24.5119	.022	-0.155	0.000541	0.02945	-0.00094	0.075	-0.92879	-10.9861	0.37
Small SUV	-0.00053	-0.1470	0	.022	-0.35	0	0	-0.00094	0.075	-0.92879	-10.9861	0.37
Large SUV	-0.00037	-0.1470	0	.022	-0.35	0	0	-0.00094	0.075	-0.92879	-10.9861	0.37
Small Pick-up Truck	-0.0005	-0.1470	0	.022	-0.35	0	0	-0.00094	0.075	-0.92879	-10.9861	0.37
Large Pick-up Truck	-0.00039	-0.1470	0	.022	-0.35	0	0	-0.00094	0.075	-0.92879	-10.9861	0.37